OPTIMIZING GROUND TIMES FOR AMC
AIRCRAFT IN AFGHANISTAN

THESIS

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Abstract

Air Mobility Command's (AMC) airlift assets that transit airfields in Afghanistan are given only a small variety of ground times in order to accomplish their mission. These ground times are based on overarching categories of missions that aircraft execute, such as cargo upload, cargo download, passenger upload, passenger download, or a combination of these. The current mission planning system uses these overarching categories to plan ground times and does not account for the exact amount of cargo or passengers. This leads to longer or shorter ground times than planned. In order to increase stability at these fields and better account for the number of sorties that can be planned into Afghanistan, a method to calculate optimal or near optimal ground times is needed.

This research creates a linear regression model that accounts for the size of cargo upload, cargo download, passenger upload, and passenger download known by the mission planner. This model can be used by the mission planners at AMC's Tanker Airlift Control Center (TACC) to increase the efficiency of planning sorties into Afghanistan. Six months of historical data is filtered and categorized and then analysis is accomplished using the JMP linear regression program. Eight scenarios are analyzed to account for C-17, C-130 and C-5 missions to Bagram AB, Kandahar AB and Camp Bastion airfields in Afghanistan. Analysis is concluded and insights are drawn regarding how to stabilize planned ground times.

Three of the scenario models are found to be significant and are validated with split data from a separate month's worth of data. All C-130 models are not significant due to many factors. The remaining insignificant models can be attributed to data system errors and unexplained variance. The use of the three significant models will increase stability in AMC planning and efficiency. In turn, our overall wartime effectiveness will be enhanced.

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To My Wife and Son

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Eric W. Bucheit Jr.

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1. Introduction

1.1. Background

Air Mobility Command's (AMC) mission statement is "Provide Global Air Mobility ... Right Effects, Right Place, Right Time" (www.amc.af.mil). Since the beginning of Operation Enduring Freedom, AMC has tried to accomplish this and has airlifted "approximately 12.5 million passengers, delivered more than 4.5 million tons of cargo, distributed more than 1.5 billion gallons of fuel, and performed nearly 133,000 patient movements" (Wilson). AMC accomplishes its airlift prowess with aircraft such as the C-17, C-5, C-130, KC-10 and KC-135. These aircraft have specific missions. The C-17, C-5 and C-130's primary missions are to deliver cargo, in many different forms, to areas around the World. The KC-135 and KC-10's primary mission is air refueling with a secondary mission of moving cargo.

This research focuses on the cargo delivered into Afghanistan. Since the bulk of the cargo is delivered from the C-17, C-5 and the C-130, the focus is on these aircraft. The C-17 can carry 102 troops/paratroops (188 troops with palletized seating), 36 litter and 54 ambulatory patients and attendants, 170,900 pounds of cargo with up to 18 pallets positions and can fly between 2,400-6,000 nautical miles (dependent on cargo weight)

without air refueling. The C-5 can carry 73 passengers, 270,000 pounds of cargo with up to 36 pallet positions and can fly up to 6,320 nautical miles (dependent on cargo weight) without air refueling. Both aircraft have a virtually unlimited range when utilizing in-flight refueling. The C-130 can carry 40,000 pounds of cargo with 6-8 pallets or 74-97 litters or 16-24 CDS bundles or 92-128 combat troops or 64-92 paratroopers, or a combination of any of these up to the cargo compartment capacity or maximum allowable weight and can fly 1200-2000 nautical miles (dependent on cargo weight) (AFPAM10-1403, Air Force Aircraft Fact Sheets).

All of these aircraft have operational restrictions in order to land at certain airfields. These restrictions are mainly determined by the size of the available runway and if the runway is stressed for a specific type of aircraft. These restrictions keep the C-5 out of many airfields in Afghanistan. It only lands at Bagram, Kandahar, and Kabul airfields. The C-17 can land on more runways, due it its smaller size and capability to land on unprepared surfaces. The C-130 is the most versatile of the three cargo aircraft and can land at almost any airfield in Afghanistan.

1.2. Problem Statement

Air Mobility Command's (AMC) airlift assets, that transit airfields in Afghanistan, are given only a small variety of ground times (slot times) in order to accomplish their mission. These are based on what overarching type of mission the aircraft are executing, i.e. cargo upload, cargo download, passenger upload, passenger download, refueling, or a combination of these missions. The current mission planning system uses these overarching categories to plan ground times and does not account for

how much cargo or how many passengers are to be loaded or unloaded. This can be seen in Table 1.1. If an aircraft has only a download or an upload, then the ground time is shorter, i.e. 1+45 for the C-17 with one event (one hour and forty five minutes). If the aircraft has both a download and an upload, then the ground time is increased, i.e. 3+15 for the C-5 with two events. These numbers were received from current Tanker Airlift Control Center mission planners and Air Force Pamphlet 10-1403.

Table 1.1 Event Planning Ground Time

Acft	1 EVENT (hours)	2 EVENTS (hours)
C-17	1+45	2+15
C-130	0+45	1+30
C-5	2+15	3+15

The use of these generic times leads to much longer or shorter ground times than planned. In order to stabilize airflow at these fields and better account for the number of sorties that can be planned into Afghanistan, a method to calculate optimal or near optimal slot times is needed. This should increase the efficiency of how troops and cargo are delivered to downrange locations. In turn, our overall wartime operations will be enhanced.

1.3. Methodology

A retrospective study is accomplished to address the problem statement. This includes historical data synchronization and linear regression methods. These are used to build a suitable model for AMC to use and more reliably predict ground times. Data

synchronization is used to merge database information into a usable format. This format is then used in linear regression software (JMP) to develop models to fit different scenarios. These scenarios include each airfield and each jet individually; therefore, there are eight models developed based on each scenario.

Table 1.2 Scenario Matrix

	Bagram Air Base	Kandahar Air Base	Camp Bastion
C-17	Scenario 1	Scenario 2	Scenario 3
C-130	Scenario 4	Scenario 5	Scenario 6
C-5	Scenario 7	Scenario 8	C-5s do not transit

The different models are needed because each jet has different ramps, parking spaces, aerial port capabilities and other variables per airfield. These other variables are set to remain constant at these fields.

The linear regression analysis checks for model adequacies, significance, multicollinearity, influence points, outliers, and other factors such as VIF, C_P, R^2 and adjusted R^2 that are defined in Chapter 2. This should satisfy the need to understand if the historical information is usable in the regression model. Following these tests, and based on the regression coefficients; a regression equation is computed and used to predict how long jets should be planned to stay on the ground per cargo and passenger loads. The cargo is accounted for in pallet positions and the passengers are counted individually.

1.4. Assumptions/Limitations

There are many assumptions and limitations that could impact this analysis and mission success. These lie within the aircraft, the aircrew operating the aircraft, the Aerial

Port crews (crews that upload and download cargo), the airspace over and on the way to the airfield, and the airfield itself. These are standard assumptions that are sometimes taken for granted, but could severely impact mission success.

The assumptions are:

- Aircrew operating the same type of aircraft have the same abilities to download all different types of cargo
- No engine running offloads or onloads are accomplished for C-17 or C-5 aircraft
- Aerial ports have the needed equipment to download and upload all types of cargo from each specific aircraft sent to its airfield
- Aerial port members have the same ability to download and upload cargo
- Airspace is open over and leading to the specific landing runway
- Runways are open without major implications to inbound or outbound aircraft, i.e. the runway is open and the taxiways to the parking spots are usable
- Weather conditions at the airport during landing windows satisfy basic Air Force Instruction 11-202V3 weather requirements
- Time to transit from landing to parking is always constant per airfield
- Time to transit from parking to takeoff is always constant per airfield
- Parking spots per aircraft are constant
- Crew planning and inspection times are constant
- Concurrent servicing of cargo and fuel is approved

Limitations impacting this study mainly come from acquiring the data to analyze the ground times of different aircraft. The major limitations are listed below:

- Not all aircrew and aerial port members have the same ability to download and upload equipment
- Data systems from which information is pulled, i.e. GDSSII and GATES are not perfect and rely on Airmen to input data correctly
    - Data is not kept for all different types of delays on the ground
    - Delay codes are considered inaccurate within GDSSII
    - Changes to the scheduled ground times are made within GDSSII while the mission is active, the schedule ground time should remain the same throughout the mission
    - Numerous data points (i.e. mission information) have more pallet positions or passengers than are possible for the aircraft to hold
    - Numerous data points have no cargo or passenger data
- No database known at this time keeps track of how much fuel each jet has uploaded and the time required for fueling

1.5. Research Objectives

The objective of this research is to build a model that accounts for the amount of cargo uploaded, cargo downloaded, passengers uploaded, and passengers downloaded. Other known delays such as a Medical Evacuation, refueling, and any other known length of delays are added separately based on specific mission requirements by the mission

planner. This model is instantiated in an EXCEL program that the mission planners at AMC's Tanker Airlift Control Center (TACC) can use to increase the efficiency of planning sorties into Afghanistan.

In order to build this model, data is needed from TACC. This data consists of how long it takes to upload and download certain amounts and types of cargo and passengers. This data can be taken from two different systems, Global Decision Support System 2 (GDSS II) and Global Air Transportation and Execution System (GATES).

GDSS II is used by every Air Force command post at airfields in Afghanistan and by the TACC. Airmen at these centers input data including: the scheduled and actual land times, take off times, and, if applicable, reasons for delay. GDSS II can be accessed by most Airmen who operate in the AMC environment to tell when incoming planes will be landing, how much cargo they have, if there is a delay, and to prepare their field for the incoming aircraft. This is an essential tool for Airmen to accomplish their jobs.

GATES is a system used by Aerial Port members to track passenger and cargo uploads and downloads. This system records cargo movement per mission identification numbers into and out of individual airports. This system tracks where cargo is currently, where it came from and where it is going.

The GATES system is used to pull information about how much cargo and how many passengers were downloaded and uploaded onto specific aircraft with specific mission numbers. This information is cross referenced with information from GDSSII of scheduled and actual ground times. A model is developed based on this information and used to improve the ground time planning system.

In order to test this model, six months of historical data are run through the model and insight is drawn as to how much the ground time planning has changed and how many more or less aircraft can be planned downrange in a given day and month. The model based on six months of historical data is then used on subsequent historical months to see if the model predicted ground times were closer to the actual ground times than the originally scheduled ground times.

1.6. Summary

Chapter one presented the background for the research, problem statement and a way ahead. This topic is very important to the future of AMC planning in theater operations. Chapter two discusses the literature for this research and focuses on applicable areas of linear regression with additional review for future research. Chapter three contains a discussion and explanation of the methodology. Chapter four captures the analysis of the information generated by the methodology. Chapter five discusses conclusions and recommendations for AMC and future research.

2. Literature Review

This chapter contains many techniques and areas of focus to analyze airflow problems and cargo loading planning techniques. Initially this problem was thought to have more of a focus on the need to understand actual airflow into and out of the Afghanistan Theater of Operations. After much study and analyzing, this problem proved amenable to analysis using a simple linear regression. This literature review has a limited discussion on the airflow into and out of the theater to enlighten future scholars on possible ways to proceed if requested or needed by AMC or other affiliates.

2.1. Linear Regression

Linear regression is a commonly used statistical technique to analyze a relationship between variables. This type of study can and is used in almost every type of field. The results have been proven and the methodology is sound. Two books are used in this review. One is "Introduction to Linear Regression Analysis" (Montgomery, Peck, Vining, 2001) and the other is "Design and Analysis of Experiments" (Montgomery, 2009). Both of these books have many good points to focus on in this analysis, but the main focus in the review is on the "Introduction to Linear Regression Analysis".

Initially, Montgomery et al. (2001) talks about data collection techniques. There are three basic methods of collecting data: a retrospective study based on historical data, an observational study, and a designed experiment (Montgomery, Peck, Vining, 2001). A historical data collection is needed in this analysis; therefore, a retrospective study is needed. There are several disadvantages of a retrospective study.

> Some of the relevant data often are missing. The reliability and quality of the data are often highly questionable. The nature of the data often may not allow us to address the problem at hand. The analyst often tries to use the data in ways they were never intended to be used. Logs, notebooks, and memories may not explain interesting phenomena identified by the data analysis (Montgomery, Peck, Vining, 2001, p.8).

These shortcomings are not all apparent in every historical observation but need to be kept in mind while conducting an analysis. Some of these problems could lead to outliers.

Simple linear regression is based on one regressor (x) and its relationship with a response variable (y). The point is to try and fit a line by using the data to show relationships and predict outcomes. This leads to the simple linear regression model:

The technique used to find β_0 and β_1 is the method of least squares; estimate the β_0 and β_1 so that the sum of the squares of the differences between the observations y_i and the straight line is a minimum (Montgomery, Peck, Vining, 2001).

2.2. Multiple Linear Regression

Multiple linear regression is a focus for this study. This is because many different regressors are needed to understand a complicated system. A simple form of this equation would be

> This is called a multiple linear regression model with k regressors. The parameters β_j (j=0,1,...,k) are called the regression coefficients. This model describes a hyperplane in the k-dimensional space of the regressor variables x_j. The parameter β_j represents the expected change in the response y per unit change in x_j when all of the remaining regressor variables are held constant (Montgomery, Peck, Vining, p.68, 2001).

Any regression model that is linear in its parameters is a linear regression model, regardless of the shape of the surface it generates.

Multiple linear regression also uses the method of least squares to determine the regression coefficients as in the simple linear regression. After accomplishing this, there needs to be a check of statistical significance in the regression model. The test for significance determines if there is a linear relationship between the response and any regressor variables. For this, an F test can be used to test the hypothesis H_o: $\beta_1 = \beta_2 = \ldots = \beta_k = 0$, and rejection criteria would be if $F_o > F_{\alpha,1,n-2}$ (Montgomery, Peck, Vining, 2001).

2.3. Checking Model Adequacy

The major assumptions in regression are that 1) the observations are adequately described by the model, 2) the errors are normally distributed, 3) the errors are independently distributed, 4) the errors have a constant, but unknown, variance and 5) that the errors have a mean of zero (Montgomery 2009). These are very important assumptions that need to be checked to legitimately make statistical inferences. Montgomery also discusses ways to work around some of these areas if they are not adequate.

To find if the observations are adequately encapsulated in the model, R^2 and adjusted R^2 are computed (Montgomery 2009). The coefficient of determination, R^2:

. “SS_T is a measure of the variability in *y* without considering the effect of the regressor variable *x* and SS_{res} is a measure of the variability in y remaining after *x* has been considered” (Montgomery, Peck, Vining, p. 39, 2001). R^2 could be considered the proportion of variation explained by x. R^2 is between 0 and 1 and the

higher the number, the more the variability is explained with 1.0 being a perfect fit. The R^2 equation can falter with numerous regressors (over fit the model and inflates R^2); therefore, adjusted R^2 was developed. The adjusted R^2 statistic penalizes the model for using many regressors. , where n is the number of observations and p is the number of regressors (Montgomery 2009).

To check for normally distributed errors, a simple test of the normal probability plot of residuals is accomplished. If the residuals fall within a specific distance from a straight line through their center, they are assumed to be normally distributed. Also, the average value for the residuals should be approximately zero (Montgomery 2009).

Checking for independently distributed error requires a plot of the residuals in time sequence. If no pattern is visible, they are assumed independent (Montgomery 2009). Historical data can be assumed to be independent due to the lack of ability to plan or record information.

To verify that the errors have a constant, but unknown, variance, a plot of residuals verses fitted (or predicted) values is used. The model is correct and the assumption holds if the residuals do not follow any pattern. The magnitude of the residuals versus the predicted values should be relatively constant across the observations and the average value of the residuals should be approximately zero (Montgomery 2009). If this is not confirmed, variance stabilizing transformations can be applied to the Y variable to try and correct the problem. This is seen when, after the transformation, the data is more symmetric and does not have a funnel or bow shape.

There are many different types of transformations. Montgomery (2009) discusses the square root, logarithmic, arcsine, reciprocal square root, reciprocal, and rank transformations. He also discusses the use of the Box-Cox Method to estimate the transformation parameter (Montgomery 2009). One additional method that he employs in his earlier work is a method of weighted least squares (Montgomery, Peck, Vining 2001). All of these methods can work for different sets of data based on their individual relationships. Finding a useful transformation can make all the difference in a good analysis.

2.4. Outliers & Multicollinearity

Detecting outliers and multicollinearity are important to any linear regression analysis. These areas can point to fundamental flaws or further areas to analyze. This additional analysis could consist of eliminating the specific data point, or could lead to information that sheds light on additional areas of interest.

Outliers are extreme observations. These points have residuals that are much larger than others. Typically they are three to four standard deviations from the mean (Montgomery, Peck, Vining 2001). These points are not representative of the rest of the data and could possibly have serious effects on the regression model. Montgomery suggests using scaled residuals, such as the studentized and R-student residuals. Once found, these points need to be investigated. Hopefully the reason for their curious behavior can be established. If there was an error in collecting the observation, this error should be fixed or the data point should be thrown out (Montgomery, Peck, Vining 2001). If no error is found and the point is just unusual, then it should be kept in the

model. “Deleting these points to ‘improve the fit of the equation’ can be dangerous, as it can give the user a false sense of precision in estimation or prediction” (Montgomery, Peck, Vining, p.154, 2001).

Specific types of outliers can be seen as leverage or influence points. These points are explicit outliers in that they affect the model differently and in a relatively exact manner. Leverage points are points that lie on the regression line and do not affect the regression equation, but will have an impact on statistics such as R^2. Influence points pull the regression equation in its direction. Therefore, it is significantly above or below the majority of the points. The knowledge of a leverage or influence point does not mean to discard, but as with other outliers, more investigation of those points needs to be made and a final determination on whether to leave in or discard should be made judiciously. Cook’s Distance test can be used to consider both the location of the point in the x-space and the response variable in measuring influence. This “uses a measure of the squared distance between the least-squares estimate based on all *n* points and the estimate obtained by deleting the *i*th point, say ” (Montgomery, Peck, Vining, p.212, 2001).

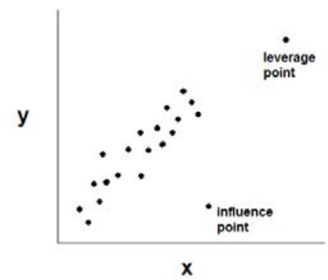


Figure 2.1 Leverage and Influence Points

Multicollinearity occurs when two or more regressors in a multiple regression are highly correlated. Montgomery states when “there are near linear dependencies among the regressors the problem of multicollinearity exists” (p. 325, 2001). This can cause the inferences based on the regression model to be flawed or misleading.

There are four primary sources of multicollinearity: “the data collection method employed, constraints on the model or in the population, model specification and an over defined model” (Montgomery, Peck, Vining, 2001, p. 326). The data collection method can cause this to occur if only a subspace of the samples is taken. Constraints on the model or in the population can also cause multicollinearity by using regressors that are correlated. Montgomery uses a reference between family income and house size as two regressors that would cause multicollinearity (2001). Model specification by the choice of model can cause multicollinearity. If this occurs, look at the specific reasons a model was chosen. An over defined model has more regressors than observations (Montgomery, Peck, Vining 2001).

Multicollinearity is one reason why large variances and covariances can occur for the least-squares estimators of the regression coefficients. “This implies that different samples taken at the same *x* levels could lead to widely different estimates of the model parameters” (Montgomery, Peck, Vining, 2001, p.329). This can also produce least-squares estimates that are too large in absolute value.

Detecting multicollinearity is essential to understanding the multiple regression model. Montgomery et al. (2001) discusses several techniques to include, the examination of the correlation matrix, variance inflation factors (VIF), and the eigensystem analysis of $X'X$. The examination of the correlation matrix involves looking at the off diagonal elements of the $X'X$ matrix. If the absolute value is close to 1.0, then there is a strong linear dependence. “The VIF for each term in the model measures the combined effect of the dependencies among the regressors on the variance of that term” (Montgomery, Peck, Vining, 2001, p.337). One or more large

VIFs indicate multicollinearity. Montgomery et al. (2001) states from practical experience that if a VIF exceeds 5 or 10, then the associated regression coefficient is poorly estimated because of multicollinearity. The eigensystem analysis of the $X'X$ matrix measures the extent of multicollinearity in the data. “If there are one or more near-linear dependencies in the data, then one or more of the eigenvalues will be small” (Montgomery, Peck, Vining, 2001, p.339).

Montgomery et al. (2001) discusses multiple ways to deal with multicollinearity. This can be accomplished by collecting additional data, model respecification, or ridge regression. Collecting additional data has been suggested as the best method to combat multicollinearity (Montgomery, Peck, Vining 2001). This should be collected in order to break up the multicollinearity in the model.

Although multicollinearity can produce poor estimates of the individual model parameters, it does not necessarily imply that the fitted model is a poor predictor. “If predictions are confined to regions of the x-space where the multicollinearity holds approximately, the fitted model often produces satisfactory predictions” (Montgomery, Peck, Vining, 2001, p.330).

2.5. Variable Selection & Model Building

Variable selection and model building are integral to analysis. There are many methods that Montgomery discusses to find the best regression equation, and there are advantages to all of them. Some of the ways to measure and determine the best fit and build the model are by using the coefficient of determination (R^2), adjusted R^2, residual

mean square (MS_{res}), Mallows's C_p statistic, and AICc. R^2 and adjusted R^2 were previously discussed.

The residual mean square is . The goal of this is to minimize MS_{res} and this also coincides with adjusted R^2 when it is at its maximum. Mallow's C_p statistic is related to the mean square error of a fitted value and looks for bias in the model, . Montgomery et al. (2001) states small values of C_p are desirable. Mallow (1973) states that minimizing C_p is similar to a stepwise regression algorithm and that the smallest or negative $C_p - p$ is a good fit. Azen and Budescu (2009) show that $C_p \approx p$ and that a small difference shows a good fit with no bias and models with $C_p > p$ have some bias.

Akaike's corrected information criterion (AICc) is a biased corrected version of Akaike's information criterion (AIC) (Lindsey and Sheather, 2010).

$$\mathrm{AIC} = n \log \frac{\mathrm{RSS}}{n} + 2k + n + n \log(2\pi) \; ; \quad \mathrm{AIC_C} = \mathrm{AIC} + \frac{2(k+2)(k+3)}{n-(k+2)-1}$$

As the criterion decreases, the model becomes more desirable. This is measured by the maximized log likelihood of the predictor coefficients and error variance (Lindsey and Sheather, 2010). This number does not have a value in magnitude that is sought-after, but the lowest value of all the AICc is the most desirable.

There are many computational techniques for variable selection. Montgomery discusses trying all possible regressions and stepwise regression. The all possible regression method is made easier with strong computer programs such as JMP and

efficient algorithms. Montgomery et al. (2001) discusses that with less than 30 regressors, the solve time is relatively easy with the all possible regressions approach.

Stepwise regression breaks down into three specific areas: forward selection, backward elimination and stepwise regression (a combination of the first two) (Montgomery, Peck, Vining, 2001). Forward regression starts with zero regressors in the model. One regressor is added to the model at a time. The first regressor selected for entry is the one with the largest simple correlation with the response variable. This regressor is entered if its F statistic exceeds a specified F value. The second regressor picked for entry is the one with the largest correlation with the response after adjusting for the effect of the first regressor, and if its F statistic exceeds the specified F value, it is also added (Montgomery, Peck, Vining, 2001). This continues until the next regressor with the largest correlation does not surpass the specified F value.

Backward elimination uses the partial F statistic as well. The partial F statistic is computed for each regressor as if it were the last variable to enter the model. The smallest of these partial F statistics is compared with a preselected F value, and if it is less than that value it is removed. This continues until one regressor's F value is not below the specified F value for elimination (Montgomery, Peck, Vining, 2001). Stepwise regression combines both of these methods and needs an F value for including and another F value for eliminating from the model. This is a modification of forward selection in that it starts with zero regressors and adds them as in the forward selection method. But following the inclusion, the backwards method is checked to see if the previous regressor should be eliminated. Frequently the choice of the F value to enter is higher than the F value to

leave; therefore, it is “more difficult to add a regressor than to delete one” (Montgomery, Peck, Vining, 2001, p.314).

2.6. Model Validity

Montgomery discusses three validation techniques for regression models. These are, 1) “analysis of the model coefficients and predicted values including comparisons with prior experience, physical theory, and other analytical models or simulation results. 2) Collection of new (or fresh) data with which to investigate the model’s predictive performance. 3) Data splitting, that is, setting aside some of the original data and using these observations to investigate the model’s predictive performance” (Montgomery, Peck, Vining, 2001, p.530).

Analysis of the model coefficients and predicted values should be studied to determine if they are stable and their signs and magnitudes are reasonable. “Previous experience, theoretical considerations, or an analytical model can often provide information concerning the direction and relative size of the effects of the regressors” (Montgomery, Peck, Vining, 2001, p.531). The VIF can also be used as a guideline as discusses previously.

Collecting fresh data is the most effective way of validating a regression model with respect to its predictive performance (Montgomery, Peck, Vining, 2001). If the model gives accurate predictions of the new data, these confirmatory runs will be seen as evidence that the model works. Montgomery et al. (2001) recommends at least 15-20 new observations to get a reliable assessment of performance.

Splitting the data is acceptable if collecting new data is not possible. When this happens, the data needs to be split into two parts, the estimation data and the prediction data (Montgomery, Peck, Vining, 2001). Careful consideration as to what data goes into each category is needed. A disadvantage of this method is that it reduces the precision with which the regression coefficients are estimated (Montgomery, Peck, Vining, 2001, p.537).

2.7. Integer Programming Techniques

Integer programming techniques to solve air traffic flow management problems have been studied and published in many journals. Integer programming has advantages in this type of study. One is that, most of the time, a closed form solution can be found. Another is that the known constraints can usually be accounted for accurately and updated in a timely manner. A drawback is that, due to the size of the network and problem, not all constraints can be accounted for.

Bertsimas and Stock (1998) considered the air traffic flow management problem for commercial aircraft and used an integer programming method to increase optimization of air traffic. They built a model that accounted for the capacities of the National Airspace System as well as capacities at individual airports. Then, they solved a large scale realistic sized problem with several thousand flights which significantly improved the state of the system.

This study included a reduced problem specific to a ground holding problem. This special case involved only the departure and arrival airport and had significant

computational advantages over the larger problem. The ground hold problem is in line with optimizing ground times in Afghanistan.

Baker et al.'s (2001) article on optimizing military airlift used the same premise and included a mathematical formulation with very specific constraints. One of these constraints dealt with airfield parking and servicing capacity constraints. These mainly deal with the number of parking spots at the airfield and if fuel or other services are available. Their technique and constraining process are useful for minimizing ground times in Afghanistan.

One of the most recent and notable articles is "An integer programming approach to support the US Air Force's air mobility network" by Koepke et. all (2008). This research extended Bertsimas and Stock's study to the Air Force. Koepke et al. used a maximum number of jets on the ground compliance formula (MCF) in order to suggest how to delay aircraft on the ground to avoid a violation of multiple constraints. This formulation takes into account constraints based on the priority of the mission, diplomatic clearances, hazardous cargo, and time delays.

2.8. Simulations

Simulation methods that deal with the mobility airlift problem mostly encompass the entire flow of cargo and aircraft from the point of embarkation to the point of debarkation. These simulations are very intricate, but do not delve into the preciseness of the exact amount of time one aircraft should spend on the ground at a specified location.

Examples of these simulations are MASS (Mobility Analysis Support System) and AMOS (Air Mobility Operations Simulator).

The main simulation used predominantly by AMC is the AMOS. This is a discrete-event worldwide airlift simulation model used in strategic and theater operations to deploy military and commercial airlift assets (Wu et al., 2009). It is favored because of its tremendous flexibility and ability to handle uncertainty. But, this simulation method requires significant input by the user to specify a series of rules to obtain realistic behaviors.

2.9. Stochastic Models

Ball et al. (2003) developed a stochastic integer program with dual network structure and applied it to the ground holding problem. This paper analyzed a generalization of the classic network flow model. It also shows that the matrix underlying the stochastic model is a dual network. “Thus the integer program associated with the stochastic model can be solved efficiently using network flow or linear programming techniques” (Ball et al., 2003).

Mukherjee and Hansen (2007) developed a dynamic stochastic model for the single airport ground handling problem. Their stochastic model has the ability to account for uncertainty and is able to update information based on evolving forecasts. Basically, it is an optimization model that assigns ground delays to individual aircraft to optimize some objective related to quantities of airborne and ground delays. This allows for revised ground delays for flights that have not taken off to their next location. The uncertainty in this model is addressed by considering a finite set of potential scenarios of

how the airfield arrival capacity may develop. This uncertainty is easier to understand in the commercial environment where weather is the major uncertainty. In a combat situation, there are many more uncertainties that will arise as aircraft come into and out of theater.

2.10. Summary

Chapter two summarized literature used in this field and what is used in this research. The main topics included linear regression and applicable themes in that area of study. Additional areas of study are incorporated and can be used in future research. Chapter three uses the linear regression topics and expounds on how they are used for this specific research.

3. Methodology

3.1. Data Synchronization

Two data bases are used to gather needed information and incorporate all of the data to analyze the problem. These data bases include the Global Decision Support System 2 (GDSS II) and the Global Air Transportation and Execution System (GATES). These two data bases are independent systems that are integrated for this analysis.

GDSSII provides an enormous amount of information to the Air Force about specific missions that are accomplished around the world. A subset of this information includes the scheduled arrival time per mission, scheduled departure time per mission, actual arrival time per mission, actual departure time per mission, mission identification number, arrival location (International Civil Aviation Organization, ICAO), previous location (ICAO), next location (ICAO), aircraft type (Mission Design Series, MDS), Total Passengers (Pax), Total Cargo, and delay remarks. All of this information is important for this analysis and was pulled from the system for the months of January-July 2010.

GATES also provides a plethora of information to the Air Force and DoD partners about specific loads on aircraft throughout the world. The subset of GATES information that is needed for this analysis includes: mission identification number (Aerial Port of Debarkation Number (APOD) mission number), aircraft type (Mission Design Series, MDS), APOD ICAO, number of passengers, Pallet net Weights, Pallet Type, and Equivalent Pallet Positions. This critical information was pulled from the system for the months of January-July 2010.

These two databases are synchronized using EXCEL databases. GDSSII has the ability to download directly into EXCEL, and GATES uses a MSACCESS format that is downloaded into EXCEL. These databases are merged using the mission identification number from GDSSII and the APOD mission number from GATES. Pivot tables and lookup functions in EXCEL make the process easier, but this process still requires a very large number of data tables in EXCEL to properly separate and merge data. These final spreadsheets include 36 columns of information consisting of information from GDSSII and GATES. GDSSII information includes the Mission number, aircraft type, airfield, actual departure time of day (Greenwich Mean Time), scheduled time on the ground (mins), actual time on the ground (mins), total passengers and total cargo in lbs, delay codes and delay remark. GATES information includes: equivalent pallet positions for the offload (10 columns) and onload (10 columns) of basic cargo, loose stock, palletized cargo, rolling stock, standard cargo, and pallet trains of size 2, 3, 4, 5, and 6, total cargo offloaded in equivalent pallet positions, total cargo onloaded in equivalent pallet positions, passengers offloaded, passengers onloaded, total passengers, and total cargo in equivalent pallet positions.

The merging of GATES and GDSSII databases shows substantial error. Although these systems are required to be used by the Air Force and DoD, they do not match during the period studied. For example, GDSSII recorded 8687 mission numbers while GATES pulled 8369 mission numbers from January-July 2010. (GDSSII does include minor cargo and passenger information, but does not include the specific cargo and passenger data needed to accomplish this analysis). The information from Gates is broken into 6528 missions with cargo information and 4682 missions with passenger

information, where 2841 missions have both cargo and passenger information. When these databases are merged, the data must be limited to missions that are in both databases. This yields an overlap of 7342 mission numbers from GDSSII and GATES that have cargo or passenger information. This can be seen in Figure 3.1.

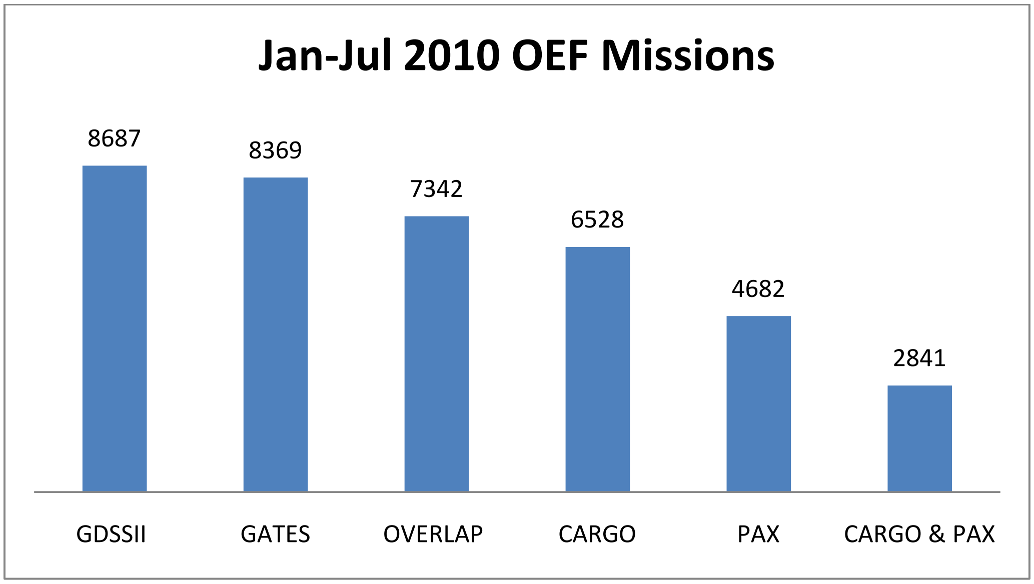


Figure 3.1 Data Base Merging

This data is broken down by aircraft type and airfield. This reduces variance based on taxi time, cargo capacity, aircraft capabilities, aerial port capabilities at each airfield, and other basic mission issues that are specific to each jet at each airfield. Therefore, eight sets of data are analyzed. These sets included three aircraft types (C-17, C-5 and C-130) at three airfields (Bagram AB, Kandahar AB, and Camp Bastion Afghanistan). Note, C-5s do not transit Camp Bastion. Table 3.1 lists the data sets.

Table 3.1 Data Base Description

	Bagram Air Base	Kandahar Air Base	Camp Bastion
C-17	Data Base 1	Data Base 2	Data Base 3
C-130	Data Base 4	Data Base 5	Data Base 6
C-5	Data Base 7	Data Base 8	C-5s do not transit

Data splitting is used because all data are historical and there are seven months of data with thousands of data points. Six months of data, January through June, are used to build the model. The seventh month is used to validate the models. 6541 total lines of data from January through June are sifted through for useful mission information. The initial data statistics are shown in Table 3.2.

Table 3.2 Lines of data per airfield per aircraft type

	Bagram Air Base	Kandahar Air Base	Camp Bastion
C-17	895	839	789
C-130	2132	1275	419
C-5	78	114	C-5s do not transit

Further pruning is accomplished based on delay codes and delay remarks of missions in GDSSII. Delay codes are numbers that should correspond with different reasons for late departures. After analyzing thousands of lines of data, this set of supposedly easy to use information is deemed unusable. This is due to hundreds of the same delay codes being used with conflicting delay remarks, i.e. delay code 201 would have a delay remark of “no delay” or delay from “previous station”. Therefore, each

individual delay remark needed to be reviewed and filtered for usefulness. If the subject matter expert (SME) thinks the delay remarks cause a significant delay, then that line of data is unusable. Many of the delay remarks include delays for maintenance, human remains movement, weather, flight planning delays/HHQ taskings, ramp freezes, MEDEVACs, double blocking, fueling, ATC congestion, specific user delays to include distinguished visitor movements, closure of the runway for hostile fire and many other reasons.

Table 3.3 Lines of data without delays

	Bagram Air Base	Kandahar Air Base	Camp Bastion
C-17	635	673	649
C-130	1456	822	323
C-5	52	79	C-5s do not transit

Additional pruning needs to occur for lines that do not have cargo or passenger information (e.g. the mission shows zero cargo and zero passengers moved). This requires sorting by total cargo and then sorting by total passengers. This further lowers our usable data as shown in Table 3.4.

Table 3.4 Lines of data with cargo/passenger information without delays

	Bagram Air Base	Kandahar Air Base	Camp Bastion
C-17	529	565	589
C-130	1251	728	287
C-5	27	48	C-5s do not transit

Other areas where pruning is needed are data lines showing more pallet positions or passengers carried than the specific airframes can actually carry and duplicate mission numbers. Data lines with more cargo or passengers are easily deleted. Some duplicate mission numbers also have duplicate cargo information, but different ground times. These missions are individually examined and eliminated based on delay remarks. This subsequently lowers the available data to the numbers in Table 3.5.

Table 3.5 Lines of data with cargo/passenger information without delays

	Bagram Air Base	Kandahar Air Base	Camp Bastion
C-17	439	485	570
C-130	736	429	195
C-5	27	48	C-5s do not transit

Supplementary pruning is also accomplished based on actual ground times. It is observed that many mission numbers are associated with very small ground times but still offload and onload a significant amount of passengers and/or cargo. These missions are intertwined with engine running offload and onloads. It is also observed that many missions with typical offloads and onloads are on the ground for an extended period of time with no remarks or delays. These missions are deemed by the SME to be unrealistic and to have an error that is unexplained or undocumented.

Therefore, C-17 missions are not used with times on the ground below 60 minutes or above 360 minutes (6 hours). The SME considers 60 minutes the lowest value that a crew can taxi in, perform normal crew duties involving engine shutdown and startup, taxi out and takeoff. The SME also considers the time of 360 minutes to be the upper limit of

cargo offloading and on loading for extreme cases. One of these cases could involve the downloading and uploading a major sized helicopter. In order to use the same rational with the C-130 and C-5, the upper time limit for C-17 is used as a base to eliminate erroneous data. The C-17 upper limit is close to 2 standard deviations away from the mean for the three airfields. Therefore, for C-5s and C-130s times above two standard deviations away from the mean are considered too long on the ground and therefore have either undocumented delays or planned ground times for other reasons than cargo.

Table 3.6 Two Standard Deviations above the mean (minutes)

	Bagram Air Base	Kandahar Air Base	Camp Bastion
C-130	246	284	157
C-5	628	455	C-5s do not transit

For C-5s, the shortest ground time is only a factor for one mission (40 mins on the ground is unrealistic for a C-5 considering taxi and crew operations) and this point is eliminated. For C-130s, the shortest ground time is considered 20 minutes as the minimum time to taxi, offload or onload, and takeoff. This is used instead of 60 minutes due to the C-130s consistent use of engine running offloads and onloads. This takes the total numbers for the six month period down to where they can be introduced into JMP, see Table 3.7. The amount of data lost due to error and or delays is significant. See Table 3.8 for the percentage of usable data from January to June 2010.

Table 3.7 Lines of data after final pruning

	Bagram Air Base	Kandahar Air Base	Camp Bastion
C-17	374	383	388
C-130	574	383	173
C-5	24	43	C-5s do not transit

Table 3.8 Percent of usable data from original set from Jan-Jun 2010

	Bagram Air Base	Kandahar Air Base	Camp Bastion
C-17	41.79%	45.65%	49.18%
C-130	26.92%	30.04%	41.29%
C-5	30.77%	37.72%	C-5s do not transit

3.2. Regression

Multiple linear regression is used to determine the optimum ground time for specific aircraft at specific airfields in Afghanistan. This is based on a retrospective study with historical data from January – July 2010. While using a retrospective study, it is known that some relevant data is often missing and the reliability and quality could be questionable. This can be seen with the GDSSII and GATES databases not matching perfectly and some data missing or not considered valid by the subject matter expert.

The JMP program is used in order to accomplish regression due to the number of regressors applied to this complicated system. This is considered a linear problem due to the time it takes to offload cargo and the time on the ground in Afghanistan being considered linear.

JMP’s multiple linear regression has many steps to accomplish. First, the data must be collected and entered into a new data table. This is accomplished for all eight data sets. The data is first taken out of the 36 columns from the GDSSII and GATES merged EXCEL spreadsheets. Both columns of time on the ground in minutes are entered into the data table, with the actual times on the ground used as the Y variable.

This problem uses 22 regressors. They include varying types of cargo offloaded and onloaded at each location, along with the number of passengers offloaded and then onloaded at each station. There are ten different types of cargo that is categorized by the GATES system. They include, belly cargo (BC), loose stock (LS), rolling stock (RS), palletized cargo (PC), skid cargo (SD), and pallet trains consisting of two – six pallets tied together as one pallet (T2, T3, T4, T5, T6). This makes up 20 of the regressors (ten during offload and ten during onload), each taking a different amount of time to accomplish. Each one of these types of cargo is given an equivalent pallet position in GATES. This means that for a certain type of cargo, e.g. a HMMWV as rolling stock taking up two pallet positions on an airframe, it is counted as the number of pallet positions it displaces on each aircraft. This is the number that is used to analyze the system. Weight was initially used, but due to the variance in weight per pallet position, number of pallet positions is a much better factor for time on the ground. For example, it takes the same time, manpower and equipment to push a pallet that weighs 100 lbs as it does to push one that weighs 2000lbs. Finally, passengers offloaded and passengers onloaded are the last two regressors, each taking a different amount of time to accomplish. Passengers are counted individually.

The labels used in JMP, and for the actual columns in the EXCEL database, include the following: Sched Time on Ground mins, Actual Time on Ground mins (Y variable), BC off, LS off, PC off, RS off, SD off, T2 off, T3 off, T4 off, T5 off, T6 off, BC on, LS on, PC on, RS on, SD on, T2 on, T3 on, T4 on, T5 on, T6 on, pax offloaded, and pax onloaded. Any type of cargo followed by an "off" is considered occurring in the offload phase of operations and any type of cargo followed by an "on" is considered occurring in the onload phase of the mission.

Once the data are collected into a new data table in JMP, the computational technique of stepwise regression is used for all eight scenarios. This is accomplished by selecting the Analyze tab, then Fit Model. Then, actual time on the ground in mins is selected as the Y variable and the 22 regressors are selected as construct model effects. Next, stepwise is selected and run with p-value thresholds of 0.1 for the probability to enter and 0.05 for the probability to leave. Mixed stepwise is selected and run. Interaction of these regressors were examined initially and found to have no significance, therefore they are not considered in this analysis.

The mixed stepwise regression uses the forward selection and backward elimination together to select only the best regressors that create the strongest model. This starts with zero regressors in the model. One regressor is added to the model at a time and then checked to make sure it stays in the model. The first regressor selected for entry is the one with the largest simple correlation with the response variable. This regressor is entered if its F statistic exceeds the specified p-value threshold (0.1). Following the inclusion, the model is changed and then backwards method is checked to see if the previous regressor should be eliminated. If the F statistic is below 0.05, it

should then be eliminated. This is based on the new model; therefore, the F statistic for this new model is needed. This continues until neither the selection p-value threshold or elimination p-value thresholds are met. This creates the strongest model. This stepwise regression produces a Sum of Squares Error, Degrees of Freedom for Error, the coefficient of determination (R^2), adjusted R^2, Mallows's C_p statistic and AICc. Adjusted R^2 is closely analyzed due to the large number of regressors.

From the stepwise fit screen, Make Model is selected. This keeps actual time on the ground as the Y variable and uses the regressors selected in the stepwise regression to construct the model effects. Then, least squares is run to find the following information: Summary of fit to include, the coefficient of determination (R^2), adjusted R^2, Root Mean Square Error, Mean of the Response, Observations, an ANOVA table, parameter estimates, Residuals by Predicted plot, actual by predicted plot, leverage plots and lack of fit table.

3.3. Checking Model Adequacy

Checking the models adequacy is accomplished next. The major assumptions of regression are checked: 1) the observations are adequately described by the model; 2) the errors are normally distributed; 3) the errors are independently distributed; 4) the errors have a constant, but unknown, variance; and 5) the errors have a mean of zero (Montgomery 2009).

Checking for normally distributed errors, a simple test of the normal probability plot of residuals, is accomplished. In JMP, the Normal Quantile Plot is used as the normal probability plot of residuals. These two plots are the same, but use different scales. If the

residuals fall within a specific distance from a straight line through their center, they are assumed to be normally distributed. Also, the average value for the residuals should be approximately zero (Montgomery 2009). The specific distance is called the “fat pencil test”. If the data points fall within a pencil thickness distance, then they will be assumed normal with slight divergence at the lower and upper ends. This chart is accessed in JMP by saving the residuals as a column in the original data table. After returning to the original data table, analysis of the distribution of the new regression column is conducted and the normal quantile plot is analyzed. The residuals are examined for a mean of zero.

Checking for independently distributed error requires a plot of the residuals in time sequence. If no pattern is visible, they are assumed independent (Montgomery 2009). In this analysis, historical data is assumed to be independent due to the lack of ability to plan or record information.

To satisfy that the errors have a constant, but unknown, variance, a plot of residuals verses fitted (or predicted) values is used. The model is correct and the assumption holds if the residuals do not follow any pattern. The magnitude of the residuals versus the predicted values should be relatively constant across the observations and the average value of the residuals should be approximately zero (Montgomery 2009). This is seen in the fit of the least squares with the residuals by predicted plot. A pattern in all of the scenarios is not readily apparent. Still, transformations are accomplished to attempt to alleviate any possible patterns. The transformations discussed in Montgomery (2009) and available in JMP are the square root, logarithmic and reciprocal.

3.4. Outliers

Upon initial review there many outliers in this data. These points have residuals that are much larger than others. Typically they are three to four standard deviations from the mean (Montgomery, Peck, Vining 2001). The residuals in each scenario are analyzed and standard deviations between three and four are considered. The studentized residuals are also plotted versus predicted values to look for outliers. These points are not representative of the rest of the data and could possibly have serious effects on the regression model.

If no error is found and the point is just unusual, then it should be kept in the model. "Deleting these points to 'improve the fit of the equation' can be dangerous, as it can give the user a false sense of precision in estimation or prediction" (Montgomery, Peck, Vining, p.154, 2001). The SME decides if these points should stay in the model or be eliminated.

3.5. Multicollinearity

Multicollinearity is examined to find correlation between regressors. When "there are near linear dependencies among the regressors the problem of multicollinearity exists" (Montgomery, Peck, Vining, p. 325, 2001). This can cause the inferences based on the regression model to be flawed or misleading.

Areas for this study that are looked into are the data collection method employed and model specification. The data collection method can cause multicollinearity to occur if only a subspace of the samples is taken (Montgomery, Peck, Vining, 2001). This definitely occurs in the data due to GATES and GDSSII not matching. Therefore, some

data are lost creating a subset of the population. Therefore, some multicollinearity may be present. Model specification is also a possible source of multicollinearity and is looked at if strong correlations exist between variables.

Detecting multicollinearity is based on the examination of the factor correlation matrix and studying the variance inflation factors (VIF). The examination of the correlation matrix involves looking at the off diagonal elements of the $X'X$ matrix (Montgomery, Peck, Vining, 2001). If the absolute value is close to 1.0 then there is a strong linear dependence. In JMP, this is accomplished by using the regressors found from the stepwise regression in each scenario in JMP's multivariate analysis tool. This yields a correlation matrix and scatterplot matrix for all used regressors and the Y variable.

The VIF was examined for each scenario. One or more large VIFs indicate multicollinearity. JMP finds the VIF by using the inverse correlation matrix. This is accomplished using the same multivariate tools as in the correlation matrix and scatterplot. The diagonal elements of $(X'X)^{-1}$ are the VIF values. Values below five are considered not to have multicollinearity.

3.6. Model Validity

JMP creates a prediction expression for each scenario. This prediction expression uses the intercept and parameter estimates for the regressors found during the stepwise regression. This model is then checked using the predicted value functionality of JMP as compared to the actual times on the ground. The prediction error sum of squares (PRESS statistic) is analyzed. The PRESS statistic is the sum of the squared PRESS residuals and

measures model quality (Montgomery, Peck, Vining, 2001). Small values of PRESS are desired.

The Box-Cox transformation is used to stabilize variance issues in the data. This is accomplished by applying the Box-Cox transformation to the Y variable to correct for any possible non-constant variance. JMP allows this by selecting the Box Cox Y transformation after the regression is run. This shows a plot of the Sum of Squares Error by λ. After viewing the table of estimates, the best transformation is saved to the initial data table and reviewed.

Next, the model is analyzed with the seventh month of data that was split from the original data. This prediction expression is with each scenario's data. This results in a predicted time on the ground for each aircraft at each field. The predicted times are then compared with the actual times on the ground. A paired t test of both sets of data is accomplished to gain understanding and determine if the model is valid. Results that show no statistical difference in the predicted and actual times yield a regression model that can be applied to real world operations.

3.7. Summary

The next chapter presents results and analysis. The statistical techniques presented in this chapter are applied. Results are shown and the predictive capabilities of the various models are tested. Additional impact to AMC's worldwide airlift operations are analyzed and shown.

4. Results and Analysis

This chapter describes the results found and analysis conducted for each of the eight scenarios. First, the stepwise regression is shown, and the Sum of Squares Error, Degrees of Freedom for Error, the coefficient of determination (R^2), adjusted R^2, and Mallows's C_p statistic are reported. Next, the model is built and checked for adequacy. Then, outliers and multicollinearity are considered. Finally, each scenario's model is checked for validity.

4.1. Stepwise Regression

Stepwise regression is conducted in all eight scenarios. This is accomplished using JMP and the mixed method of stepwise regression. This gives the most suitable model based on the p-value of 0.1 for inclusion and 0.05 for exclusion. Appendix A provides the output for all eight scenarios. Table 4.1 summarizes the stepwise findings for each scenario.

Table 4.1 Stepwise Regression Results

	Scenario	R^2	adj R^2	Intercept	# Parameters	Cp	AICc	min AICc
1	**C-17 OAIX**	0.257	0.249	172.7	5	5.3	4034	4032
2	**C-17 OAKN**	0.532	0.525	167.5	7	5.2	4147	4145
3	**C-17 OAZI**	0.305	0.301	161.1	4	3.7	4965	4965
4	**C-130 OAIX**	0.109	0.102	57.9	5	-2.5	5682	5682
5	**C-130 OAKN**	0.144	0.135	105.5	5	7.9	4332	4330
6	**C-130 OAZI**	0.091	0.08	51	3	4.7	1557	1557
7	**C-5 OAIX**	0.487	0.438	364.4	3	1.7	272	272
8	**C-5 OAKN**	0	0	266.1	1	-4.7	475	475

Information in Table 4.1 illustrates that some of the models are initially better than the others. All models that are more closely examined have a R^2 above 0.25; the

other models are not continued in the data analysis. The C-130 scenarios were not continued due to low variance in their ground time based on cargo. This is based on C-130s use of engine running cargo operations and their small and quick cargo offload and onloads. Model eight is not a good model due to zero regressors making the stepwise significance for inclusion.

Adjusted R^2 is provided at in Table 4.1. In all scenarios, the adjusted R^2 closely matches the R^2. The adjusted R^2 values penalize for the addition of multiple regressors that inflate R^2. Therefore, based on the R^2 and adjusted R^2, and the eliminated scenarios for this research, models 1, 2, 3 and 7 are continued.

Next, Mallow's C_p statistic is reviewed from Table 4.1. As Montgomery et al. (2001) stated, small values of C_p are desirable. This statistic should be close to p for a good model and favorably lower in value than p. All scenarios meet this qualification with the exceptions of 1, 5, and 6, but all of the scenarios fall under the 2p to be an acceptable level of bias (Mallows, 1973). Therefore all scenarios are acceptable in regard to Mallow's C_p statistic.

Finally, AICc is evaluated as a measure of goodness of fit. All of the scenarios fall within 1-2 of the minimum AICc. This shows that there is relatively no difference between the AICc of the model and the minimum AICc. Therefore, each model can be used to make inferences on the scenarios.

4.2. Normal Standard Least Squares

The stepwise regression outcomes are put into the actual standard least squares model in JMP. This is accomplished by confirming the Y variable and regressors and

selecting the standard least squares, make model option in the stepwise regression screen. The output can be seen in Appendix B. Figures B1-B8 represent scenarios 1-8. This output includes the Actual by Predicted Plots, Summary of Fit, Analysis of Variance, Lack of Fit, Parameter Estimates and Residual by Predicted Plot. Figure B8 is blank due to the lack of regressors chosen to enter from the stepwise regression.

4.3. Model Adequacy

The information provided by JMP in the normal standard least squares is used to determine model adequacy. This is accomplished to see that: 1) the observations are adequately described by the model, 2) the errors are normally distributed, 3) the errors are independently distributed (assumed due to historical data), 4) the errors have a constant, but unknown, variance, and 5) the errors have a mean of zero.

To determine if the observations are adequately described by the model, adjusted R^2 is reviewed. Each model has specific constants that create longer or shorter times on the ground and create an environment where more variance can be explained by the model. Therefore these scenarios cannot be compared to each other based on purely R^2. The initial R^2 values for the scenarios continued are above 0.25. This is adequate for each model.

Errors that are normally distributed can be seen using the normal quantile plot from JMP. This is accomplished for models 1, 2, 3, and 7 in Figures 4.1 thru 4.4. All normal quantile plots fall within a reasonable distance from a straight line through their center (pass the fat pencil test) with allowable trailing data on the extremities. Therefore, all are assumed to be normally distributed.

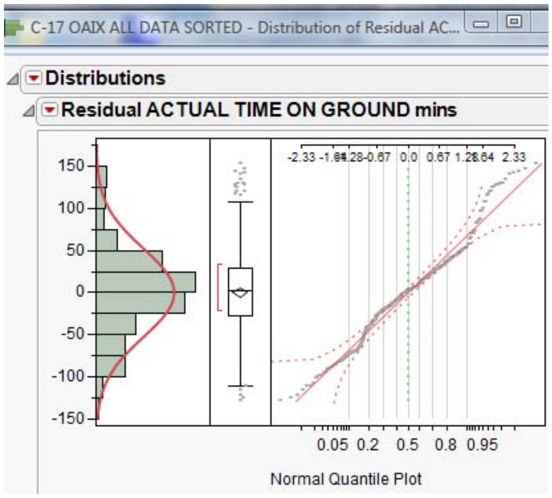


Figure 4.1 C-17 OAIX Normal Plot

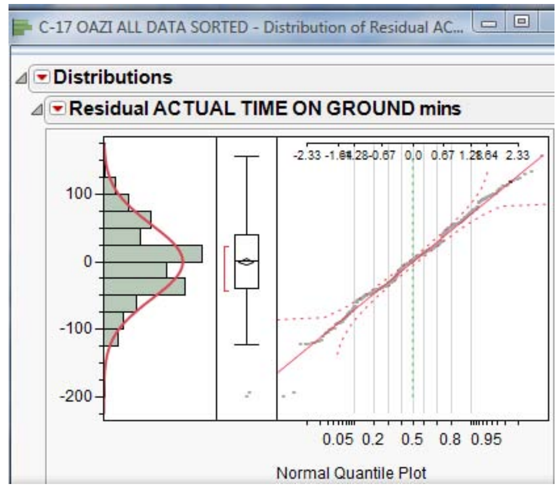


Figure 4.3 C-17 OAZI Normal Plot

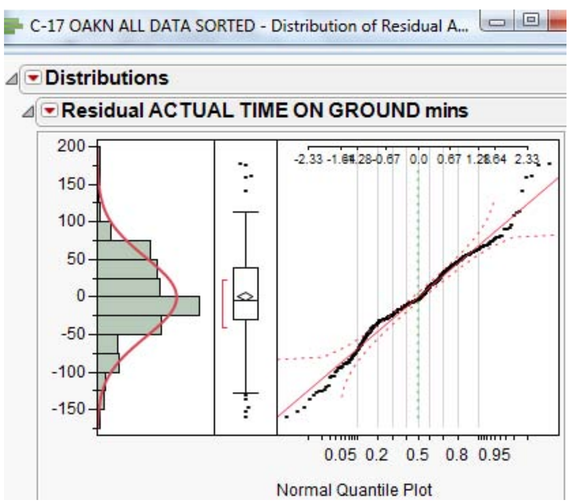


Figure 4.2 C-17 OAKN Normal Plot

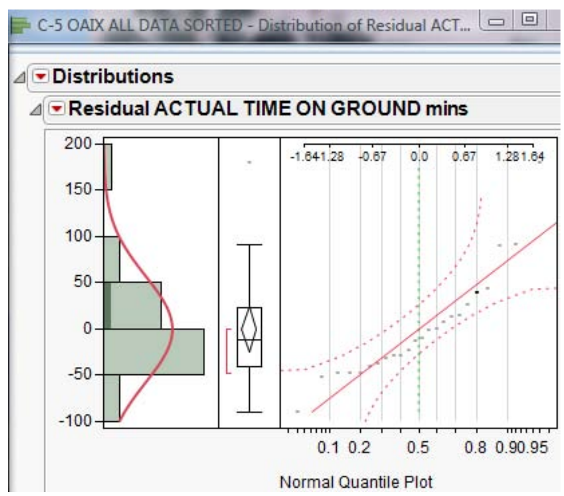


Figure 4.4 C-5 OAIX Normal Plot

JMP produces the plot of residuals versus predicted values to examine constant, but unknown, variance. This can be seen in Figures 4.5 thru 4.8. The residuals do not follow any real particular pattern such as a funnel, megaphone or bowing. There does appear to be evidence of missing data. This is inevitable when using historical data that is highly erroneous. There is also evidence of possible split data set. Looking through the data intensely, there is no evidence or similarities that are observed to split the data in

order to separate the two data sets as in Figure 4.5. Anything nonlinear should be addressed and a transformation should be accomplished to alleviate any non-constant variance. Due to the erroneous nature of the data and the slight downward trend in the data, transformations are accomplished in order to alleviate any non-constant variances.

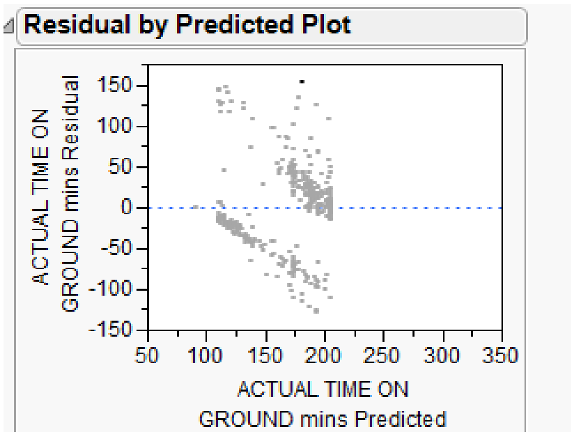


Figure 4.5 C-17 OAIX Residuals by Predicted Plot

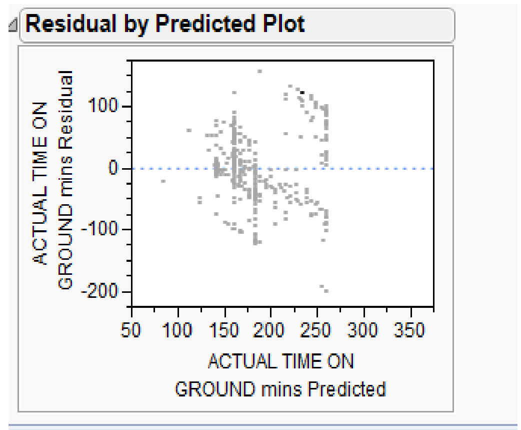


Figure 4.7 C-17 OAZI Residuals by Predicted Plot

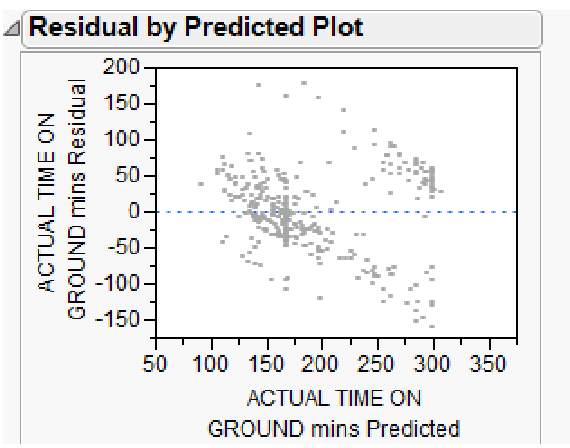


Figure 4.6 C-17 OAKN Residuals by Predicted Plot

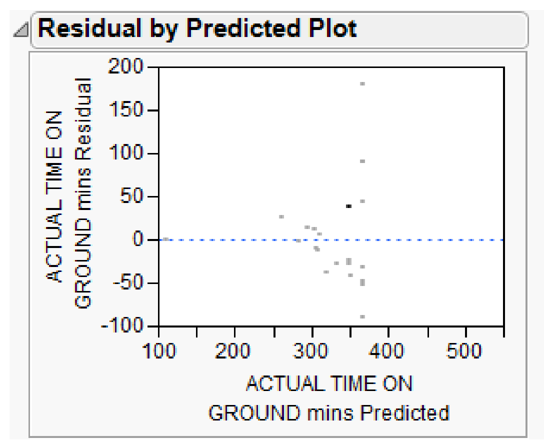


Figure 4.8 C-5 OAIX Residuals by Predicted Plot

Transformations used include the square root, logarithmic, and reciprocal. These transformations are shown below for the C-17 at OAZI. This is the case with the most variance resembling a semi-funnel shape. From looking at Figures 4.9-4.11 and

reviewing the data from the regression using the transformations, the square root transformation reduced the variance the greatest amount. Therefore, the square root transformation is used on all four remaining models.

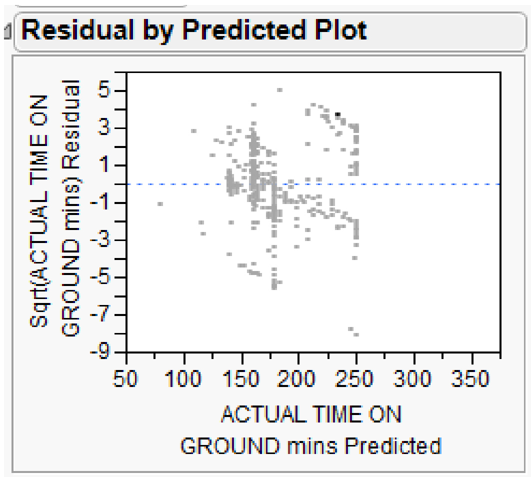


Figure 4.9 C-17 Square Root Transformation

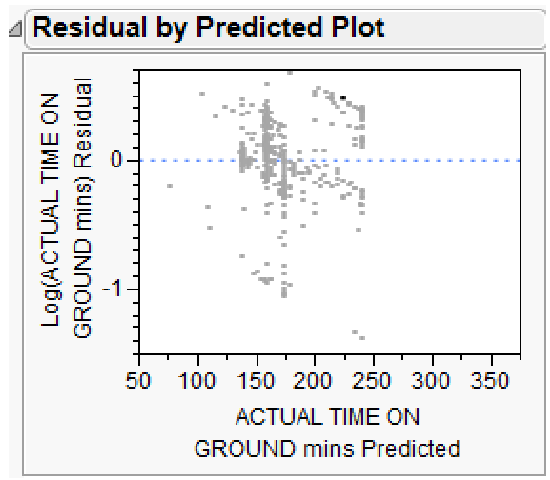


Figure 4.10 C-17 Log Transformation

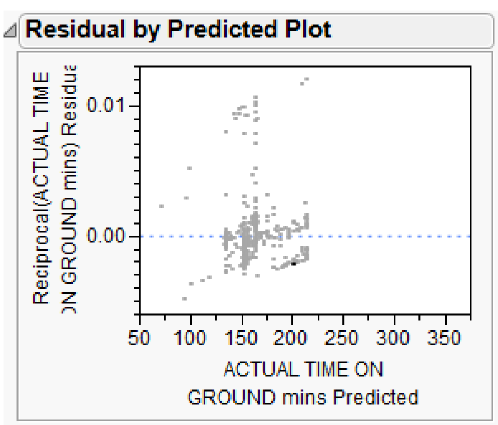


Figure 4.11 C-17 Reciprocal Transformation

The square root transformation output is displayed in Appendix C. A summary of this data is presented in Table 4.2. This table shows slight increases and decreases in R^2

and adjusted R^2 and the charts show less funneling or bowing effects. Therefore, constant variance is mostly achieved.

Table 4.2 Square Root Transformation

	Scenario	R^2	adj R^2	Intercept	# Parameters	RMSE	Obs	Variance
1	C-17 OAIX	0.271	0.263	12.89	5	2.1	374	Constant
2	C-17 OAKN	0.512	0.505	12.82	7	1.9	383	Constant
3	C-17 OAZI	0.266	0.258	12.65	4	2	457	Constant
7	C-5 OAIX	0.605	0.567	18.99	3	1.5	24	Constant

Determining the residual errors mean is accomplished by saving the residuals in a column in the JMP spreadsheet. Then, the column is transferred into the EXCEL program and averaged. In all cases, the average is zero or an extremely small number that approximates zero. The JMP distribution fitting tool also shows a mean of zero. Therefore, the last assumption holds for the four remaining scenarios and these models check for adequacy.

4.4. Outliers

Outliers are reviewed using the above three standard deviations method and studentized residuals. When residuals fall more than three standard deviations from the mean, or they are shown as outliers on the plot of studentized residuals, the actual data points are looked at for errors. If the SME believes an error has occurred, the point is eliminated. Table 4.3 shows the summary of data points found to be potential outliers from both methods. Figures 4.12-4.15 show the actual studentized residuals versus predicted values with the outliers in grey and circled.

Table 4.3 Summary of Outlier Detection

	Scenario	> 3 Std Dev	Studentized Plot	SME deteremined Error	new R^2	new adj R^2
1	**C-17 OAIX**	0	0	0	N/A	N/A
2	**C-17 OAKN**	2	0	1	0.504	0.498
3	**C-17 OAZI**	2	2	0	N/A	N/A
7	**C-5 OAIX**	0	1	0	N/A	N/A

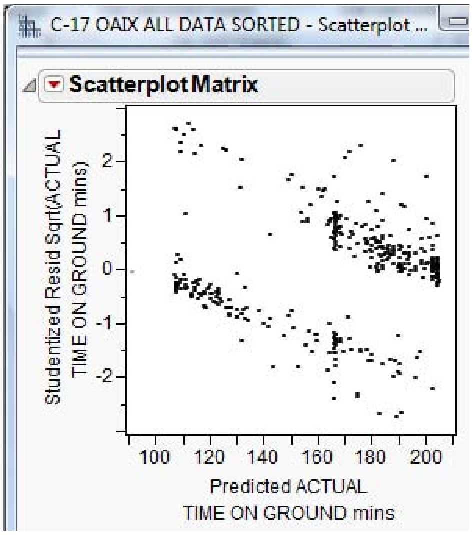


Figure 4.12 C-17 OAIX Outliers

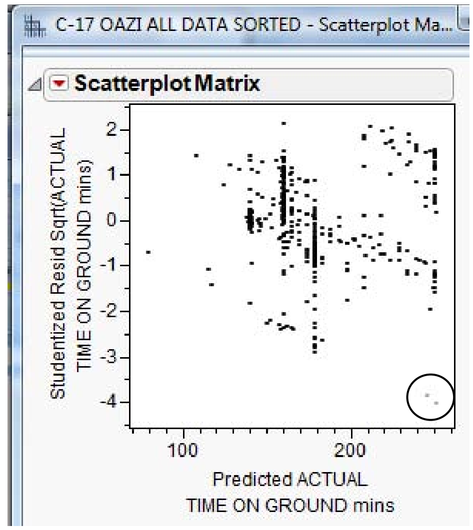


Figure 4.14 C-17 OAZI Outliers

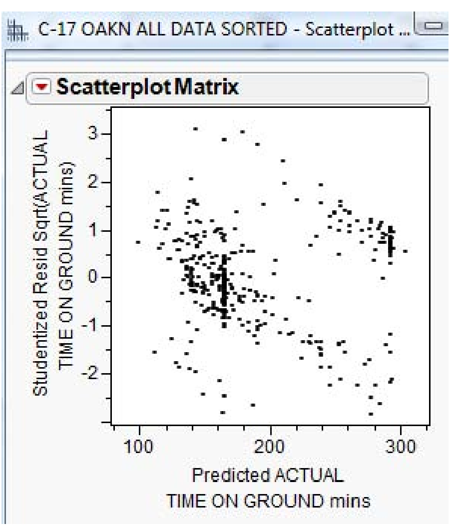


Figure 4.13 C-17 OAKN Outliers

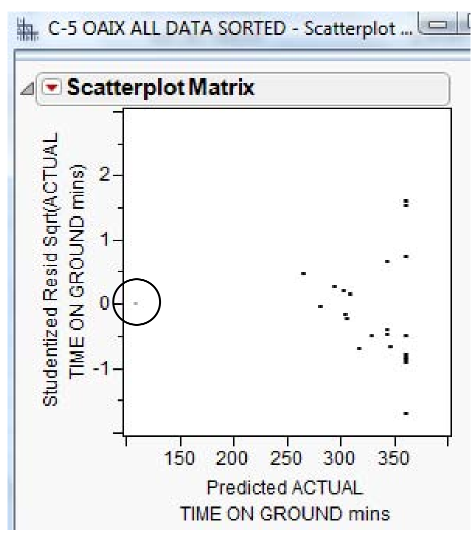


Figure 4.15 C-5 OAIX Outliers

There are no outliers found for Scenario 1 in either method. In Scenario 2, there are 2 outliers found using the standard deviation method and none found using the plot of studentized residuals verse predicted values. The SME determined that one point is erroneous and the other is unusual. The point that is erroneous listed that it had 11 equivalent pallet positions offloaded. These consisted of one T-2 and three T3 pallet trains. This is not a possible combination in the C-17 and therefore the data points are erroneous and the point should be excluded. The second point was on the ground for an extended amount of time with 135 passengers offloaded and 95 onloaded. This is slightly unusual, but not erroneous so this point is kept.

The same two potential outliers for Scenario 3 were found in both methods. These both had minimal ground times of 60 and 61 minutes with a large PC offload of 18 and 17 pallets, respectively, and no onload. The SME determined that this is not an unusual occurrence to have a large offload and no onload at OAZI and no errors were found in the data or delay remarks. Therefore, these points were maintained in the model.

The potential outlier for Scenario 7 was only found using the studentized residuals versus the predicted values. This point is deemed unusual but not erroneous by the SME. This point had a small ground time (108 minutes) and a relatively small offload (17 equivalent pallet positions) with no onload; therefore, it is slightly unusual but not erroneous.

4.5. Multicollinearity

In order to look for possible multicollinearity, the remaining four scenarios' correlation matrix, and variance inflation factors (VIF) are reviewed. The correlation

matrices are shown in Tables 4.4-4.7. The largest VIFs, taken from the diagonal of the inverse correlation matrices are listed in Table 4.8. The matrices only involve the regressors found in the stepwise regression.

Table 4.4 Scenario 1 C-17 OAIX

	ACTUAL TIME ON GROUND	PC off	RS off	T6 on	pax offloaded
Act Time on Gnd	1.0000	0.1618	0.2414	-0.0663	-0.4689
PC off	0.1618	1.0000	-0.3048	0.0001	-0.1308
RS off	0.2414	-0.3048	1.0000	0.1043	-0.3477
T6 on	-0.0663	0.0001	0.1043	1.0000	-0.0354
pax offloaded	-0.4689	-0.1308	-0.3477	-0.0354	1.0000

Table 4.5 Scenario 2 C-17 OAKN

	ACTUAL TIME ON GROUND	PC off	T2 off	PC on	RS on	T3 on	pax offloaded
Act Time on Gnd	1.0000	0.6710	0.1105	-0.1823	-0.1803	-0.0782	-0.2826
PC off	0.6710	1.0000	-0.0194	-0.0771	-0.0766	0.1207	-0.2991
T2 off	0.1105	-0.0194	1.0000	0.0796	-0.0021	-0.0239	-0.0831
PC on	-0.1823	-0.0771	0.0796	1.0000	0.0204	-0.0070	-0.1211
RS on	-0.1803	-0.0766	-0.0021	0.0204	1.0000	-0.0277	-0.0804
T3 on	-0.0782	0.1207	-0.0239	-0.0070	-0.0277	1.0000	-0.0584
pax offloaded	-0.2826	-0.2991	-0.0831	-0.1211	-0.0804	-0.0584	1.0000

Table 4.6 Scenario 3 C-17 OAZI

	ACTUAL TIME ON GROUND	PC off	RS on	pax offloaded
Act Time on Gnd	1.0000	0.5360	-0.1222	-0.2273
PC off	0.5360	1.0000	-0.0348	-0.2801
RS on	-0.1222	-0.0348	1.0000	-0.0256
pax offloaded	-0.2273	-0.2801	-0.0256	1.0000

Table 4.7 Scenario 7 C-5 OAIX

	ACTUAL TIME ON GROUND	BC off	PC off
Act Time on Gnd	1.0000	-0.5851	-0.2957
BC off	-0.5851	1.0000	-0.1376
PC off	-0.2957	-0.1376	1.0000

Table 4.8 VIF Scenarios 1, 2, 3, and 7

	Scenario 1 C-17 OAIX	Scenario 2 C-17 OAKN	Scenario 3 C-17 OAZI	Scenario 7 C-5 OAIX
Largest VIF	1.4332	2.1747	1.4581	1.9475

Multicollinearity is not seen from either the correlation matrices or inverse correlation matrices. This is seen in the correlation matrices with no regressor correlations greater than 0.34. The inverse correlation matrices show no value greater than 2.1747. Any values lower than five are not considered to show multicollinearity. Therefore, there is no evidence of multicollinearity in any of the remaining scenarios.

4.6. Model Validity

Model validity is checked in three manners. First, the prediction expression is checked using the predicted values from the test data versus the actual values using a paired t test and a 95% confidence interval. Next, the prediction error sum of squares (PRESS) statistic is analyzed for each regression scenario. Finally, the regression equation is used with the split data to compare the means of the actual versus the predicted values. A Box-Cox transformation is also attempted to increase prediction capability.

The first step involves testing the regression equations against the actual values that derived the equation. (This is similar to the residuals from the regression.) The hypothesis is that the means should be the same. The prediction expression found in the final standard least squares run for each scenario is run using the actual cargo and passenger numbers from the initial data to show the predicted values. These values are compared to the actual ground times using a paired t test with an alpha level of 0.05. They are also compared using a 95% confidence interval (CI). The 95% CI should

encapsulate zero. If there is a significant difference or the 95% CI does not encapsulate zero, the regression equation is not useful. The results from the paired t tests are displayed in Table 4.9, where H_0: $\mu = 0$ and H_a: $\mu \neq 0$.

Table 4.9 Paired t test and 95% CI for original data using regression equations

Scenario		t Stat	P(T ≤ t) two-tail	Mean difference	95% Confidence Interval
1	C-17 OAIX	1.228	0.2199	-4.35	(-9.68 , 0.98)
2	C-17 OAKN	0.703	0.4825	-3.40	(-8.69 , 1.88)
3	C-17 OAZI	1.189	0.2352	-4.09	(-9.12 , 0.92)
7	C-5 OAIX	0.103	0.9187	-2.05	(-26.5 , 22.4)

From the paired t-test performed to determine if the means are different, it can be surmised that the null hypothesis is not rejected. Also, each 95% CI included zero; therefore, the mean difference between the two data sets is not significantly greater than zero. This was a good result and should have occurred because the prediction data was used to derive the regression equation.

Next, the prediction error sum of squares (PRESS) statistic is analyzed. The PRESS statistic is found in the output of each scenario in JMP. This is chosen using the response selection. The PRESS value for each model is shown in Table 4.10. Small values of PRESS are favorable. From the PRESS statistics in Table 4.10, it is seen that all are very close to SSE. Therefore, all models have a good PRESS statistic.

Table 4.10 PRESS Statistic

Scenario		PRESS statistic	SSE
1	C-17 OAIX	1657	1626
2	C-17 OAKN	1361	1303
3	C-17 OAZI	1908	1878
7	C-5 OAIX	58	49

The final step includes using the derived prediction expressions with the split data for the month of July 2010. The regression equations should result in planned ground times that are not significantly different from the actual ground times. The hypothesis is that the means should be the same. The prediction expression found in the final standard least squares run for each scenario is run using the actual cargo and passenger numbers from the July data to show the predicted values. These values are compared to the actual times using a paired t test with an alpha level of 0.05. They are also compared using a 95% confidence interval (CI). The 95% CI should encapsulate zero. If there is a significant difference and the 95% CI does not encapsulate zero, the prediction expression is not useful. The distribution of the actual ground time in July was also analyzed and is similar to the original data. The prediction expression for each scenario is shown in Table 4.11. The results from the paired t tests are displayed in Table 4.12, where H_0: $\mu = 0$ and H_a: $\mu \neq 0$.

Table 4.11 Prediction Expressions Square Root Transformation

<table>
<tr><th></th><th>Intercept (minutes)</th><th>BC off</th><th>PC off</th><th>RS off</th><th>T2 off</th><th>PC on</th><th>RS on</th><th>T3 on</th><th>T6 on</th><th>Pax off</th></tr>
<tr><td>C-17 OAIX</td><td>12.89</td><td></td><td>0.0739</td><td>0.1002</td><td></td><td></td><td></td><td></td><td>-0.796</td><td>-0.0161</td></tr>
<tr><td colspan="11">= 12.89 + 0.07387 * PC off + 0.1002 * RS off - 0.7955 * T6 on - 0.01606 * Pax off</td></tr>
<tr><td>C-17 OAKN</td><td>12.82</td><td></td><td>0.2382</td><td></td><td>0.2657</td><td>-0.119</td><td>-0.1962</td><td>-0.848</td><td></td><td>-0.0066</td></tr>
<tr><td colspan="11">= 12.82 + 0.2382 * PC off + 0.2657 * T2 off - 0.119 * PC on - 0.1962 * RS on – 0.848*T3 on - 0.0066 Pax off</td></tr>
<tr><td>C-17 OAZI</td><td>12.65</td><td></td><td>0.1762</td><td></td><td></td><td></td><td>-0.4077</td><td></td><td></td><td>-0.0052</td></tr>
<tr><td colspan="11">= 12.648 + 0.1762 * PC off - 0.4077 * RS on - 0.00516 * Pax off</td></tr>
<tr><td>C-5 OAIX</td><td>18.99</td><td>-0.532</td><td>-0.092</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="11">= 18.99 - 0.5318 * BC off - 0.092 * PC off</td></tr>
</table>

Table 4.12 Paired t test and 95% CI for Prediction Expressions with July data

Scenario	Aircraft Airfield	Obs	t Stat	P(T ≤ t) two-tail	Mean difference	95% Confidence Interval
1	C-17 OAIX	197	4.3	0.00002	-21.3	(-29.2 , -13.3)
2	C-17 OAKN	185	-1.8	0.07	12.24	(2.5 , 21.98)
3	C-17 OAZI	65	0.14	0.89	1.48	(-17.2 , 20.2)
7	C-5 OAIX	13	-2.1	0.057	80.78	(-1.8 , 163.4)

From these results, it is apparent that models for Scenarios 3 and 7 are the only two models that have significance with both the t test and the 95% CI. This is displayed by both the two-tail being above 0.05 and the 95% CI including zero. Scenario 2 shows significance in the t test, but not in the 95% CI.

Next, a Box Cox transformation is conducted to alleviate more variance and increase the predictability of the models. This is accomplished through JMP using the best Box Cox transformation that JMP produces. Table 4.13 shows the results from using a Box Cox transformation instead of the Square Root transformation.

Table 4.13 Paired t test and 95% CI using Box Cos Transformation

Scenario	Aircraft Airfield	Obs	t Stat	p(T ≤ t) two-tail	Mean difference	95% Confidence Interval
1	C-17 OAIX	197	4.24	0.000028	-21.02	(-29.0 , -13.04)
2	C-17 OAKN	185	-1.51	0.13	10.25	(0.38 , 20.13)
3	C-17 OAZI	65	-0.29	0.77	3.05	(-15.6 , 21.7)
7	C-5 OAIX	13	-1.57	0.14	61.46	(-23.4 , 146)

The Box Cox slightly increases the significance in Scenarios 2 and 7, but decreased in Scenario 3.

The prediction expression values for Scenarios 2, 3, and 7 are also compared with the actual ground times in July to realize potential savings in ground time. During the months of January-June 2010, the average early and late times over all missions were 36 minutes early and 45 minutes late. The models predicted values over the month of July decreases the minutes early to 28 and the minutes late to 39. This does not look like a significant change, but over the course of a month, with around 200 C-17 and C-5 missions through the Scenarios, this equates to lowering the error in planning by 4445 minutes or 74.1 hours.

This does not necessarily mean that throughput will be increased or decreased. As seen with the prediction expressions in Table 4.9, the intercept (once squared) for the C-17 is averaging 2.73 hours ± regressors and the C-5 is averaging 6 hours ± regressors on the ground. This is an increase from the maximum planning ground times of 2.25 for C-17s and 3.25 for C-5s. Actual values for throughput follow: C-17s at Camp Bastion average 3 C-17s per day with a maximum in 2010 of 9 C-17s in one day, C-17s at Kandahar AB average 4 C-17s per day with a maximum in 2010 of 13 C-17s in one day, and C-5s at Bagram AB average 1.4 C-5s per day with a maximum in 2010 of 5 C-5s in one day. The average and maximum amount of aircraft transiting these airfields on any given day leave room for the possible increased ground time. Using the models with maximum on the ground values at each location, it is seen that the maximum throughput for a given day for C-17s at Camp Bastion is 18 C-17s, for C-17s at Kandahar AB is 26 C-17s, and for C-5s at Bagram AB is 8 C-5s. These numbers are almost all over double the maximum amount of aircraft throughput in 2010. Therefore, throughput should not be

affected by the new model and the entire process should become more predictable and stable.

4.7. Summary

The results from Chapter 4 show that ground times can be accurately predicted using historical cargo data and ground times in three of the eight scenarios. The remaining five scenarios do not have significance to predict ground times. Scenarios 3 and 7 hold the strongest significance with both the t test and the 95% CI showing accurate prediction capability. Scenario 2 shows significance in the t test but not the 95% CI. This result is suitable to be used in future predictions. Therefore, the linear regression model built for Scenario 2 could be used to accurately predict C-17 ground times at OAKN. Chapter 5 summarizes the conclusions drawn from this research, outlines the obstacles to implementation of results, and suggests future areas of research that broaden the scope of this research effort.

5. Discussion

5.1. Conclusion

Cargo aircraft provide essential military supplies to Afghanistan around the clock. Accurate scheduling of ground times in theater is critical to providing needed supplies to combat troops in an orderly manner. While focusing on historical data from the GATES and GDSSII data systems, a linear regression model was developed to model accurate ground time prediction using three different aircraft and airfields, with eight total scenarios. Three of these scenarios resulted in useful models that were validated using split historical data. These scenarios give the mission planners at TACC a more accurate tool to predict ground times. These can be used in the future to stabilize ground times in theater and schedule aircraft in a more accurate and efficient manner.

5.2. Unexplained Variance

Throughout this study, there were some factors during some phases of the mission from landing to takeoff that were assumed constant. These factors may not have been exactly constant and therefore could have led to unexplained variance. The phases include landing, taxiing into park, offloading, onloading, taxiing for takeoff, and takeoff, that led to unexplained variance that impacted some scenarios. Some of the factors could include motivation in either aerial port crews or aircraft crews, aerial port overtasking, and deployment rotations to name a few.

Motivation by an aerial port crew or an aircraft crew can lead to significant variance. For example, if the aerial port and the crew are very motivated, the ground time could be minimal. This is especially the case if the crew requests an early takeoff from

TACC. Conversely, a not so motivated port crew and aircraft crew could lead to much longer ground time than is expected. Any combination of these factors will lead to unexplained variance that definitely affects the outcome of this type of model.

Aerial port overtasking is another factor of unexplained variance. This could result from numerous complications. One factor is not enough ground time for one aircraft on the ground. Another is a severe maintenance problem. Both of these can back up the entire field for hours or days. Other factors could include under manning or over manning of aerial port crews.

Deployments are a constant cause of variance in theater. Four to six month deployments result in a learning curve for all Airmen that handle this process. Great lengths are taken to alleviate any of this learning curve, but it still occurs in the system and is mostly unknown during this analysis.

5.3. Errors in Data Bases

The GATES and GDSSII data bases have a large amount of error. This can be seen in almost all aspects of the system. Main areas of error were due to controllers changing scheduled times in GDSSII, GATES not accurately depicting significant differences in cargo type, or erroneous or missing delay remarks.

Some results were not able to be drawn due to controllers changing scheduled takeoff times in the system. If the mission is slipped for some reason while on the ground, the scheduled takeoff time should not be changed. The actual takeoff time will reflect this and the delay codes or remarks should give the reason for the change. This is a large

source of error and eliminated a potential avenue to explore scheduled ground times versus actual ground times in regards to the cargo on board.

The cargo needs to be better defined in GATES. The rolling stock data should be changed to include three significantly different types of cargo as well as particular outsized cargo, which takes a significantly longer amount of time to offload and upload. This would eliminate a large amount of variance in offload and upload times.

Rolling stock needs to account for drivable rolling stock, rolling stock that needs to be winched on and off the aircraft, and rolling stock that needs shoring. All three of these types of rolling stock take significantly different amounts of time to onload and offload. For example, drivable rolling stock (i.e. cars) can be easily offloaded, while a heavy power cart may need to be winched or towed onto the aircraft. Shoring is needed when the clearance of the vehicle going on or off the aircraft is too low for the angle of the ramp, therefore pieces of wood are needed to decrease the angle of the cargo ramp. This takes a longer time to organize and put together. Therefore, clumping all of these items into one category is not useful for this analysis.

Helicopters and other outsized cargo known to have a longer onload or offload time also need to be categorized differently. This is due to the increased amount of time needed to safely move such cargo. This would reduce error and variance in the system.

5.4. Limitations

The significant models should be used by experienced mission planners. Not all scenarios are derived and tested throughout the results. For example, there is an error bound that needs to be assessed by the individual mission planner that they see as

acceptable for the mission at hand. Some ground times from these equations may seem very long due to certain regressors that add significant time if the aircraft is entirely full of one type of cargo. This should be scrutinized by AMC/A9 in the accreditation phase.

There are definitely many more factors that the mission planners may need to consider when determining ground time. The results from the models should be used as a base from which the mission planner can expound. Some factors may occur simultaneously, while others may require additional ground time when cargo loading and unloading are completed. This is up to the individual mission planner, and eventually, up to the aircraft commander to implement the appropriate ground time in a safe manner.

5.5. Recommendations

This analysis resulted in many recommendations. They range from improving the accuracy of data collection, additional items for data collection, method of inputting data, method to schedule C-130 ground times specifically, and the use of the resulting models. All of these recommendations would enhance USTRANSCOM operations around the world.

Throughout this study, it was noted that many improvements in the data collection process would have led to more significant results. This can be seen from inaccurate data points throughout both databases. A more stringent approach to accurate data collection needs to be made by USTRANSCOM. The amount of erroneous data in the system, at a minimum, cost the tax payers millions each year. Effective data collection could reduce the amount of Aircraft needed in theater by helping to build more accurate models and analytical tools.

Additional data needs to be collected. This data includes the time Aerial Port begins offload, finishes offload, begins onload, and finishes onload. These times, along with relatively constant times for taxi and crew duties, could be analyzed with total time on the ground to determine a better fit for the ground time model.

Data collection should be improved using a more reliable system. This should involve some type of electronic device tied to the current system. Alternatively, a more updated data system that is taken with aerial port crews on every offload and onload could be used. The port crews could verify all cargo present and record the start and stop times of the offloads and onloads. This device could transfer the data electronically into the database and therefore alleviate the current transfer error. This type of technology can be seen on the C-17. The C-17 is equipped with a computer system that can automatically report land times, fuel on board, and takeoff times to TACC. This data collection capability and emphasis needs to be transferred to all aspects of the Air Mobility Command process to include port crews.

C-130s should use the current system they have in place. The current C-130 system uses a historical database of how long specific types of cargo loads have taken. The Combined Air Operations Center C-130 mission planners apply these times to predict relatively accurate ground times. This success is also due to the C-130's small cargo loads. C-130s generally have short and almost identical ground times no matter what type or how much cargo is offloaded or onloaded. This resulted in no significance in the linear regression models. The other components of ground time and the C-130's tendency to conduct engine running offloads and onloads are more influential in determining ground times. Since these times are mostly constant for actions not including

loading and unloading, ground times are mostly identical for all types of cargo. Therefore, the current system already creates a stable environment with the subject matter experts planning missions.

The significant models should be used by AMC/A9. Once accredited by AMC/A9, these models should be used by TACC in a test manner. The results of these models should create a more accurate account for ground times for C-17s at Kandahar and Camp Bastion and C-5s at Bagram. Although significance was not found in all models, they should be used when applicable to create a more stable air mobility system. Not counting the C-130s, there were a total of five scenarios. Three of the models for these scenarios were found to be significant.

5.6. EXCEL Based Tool

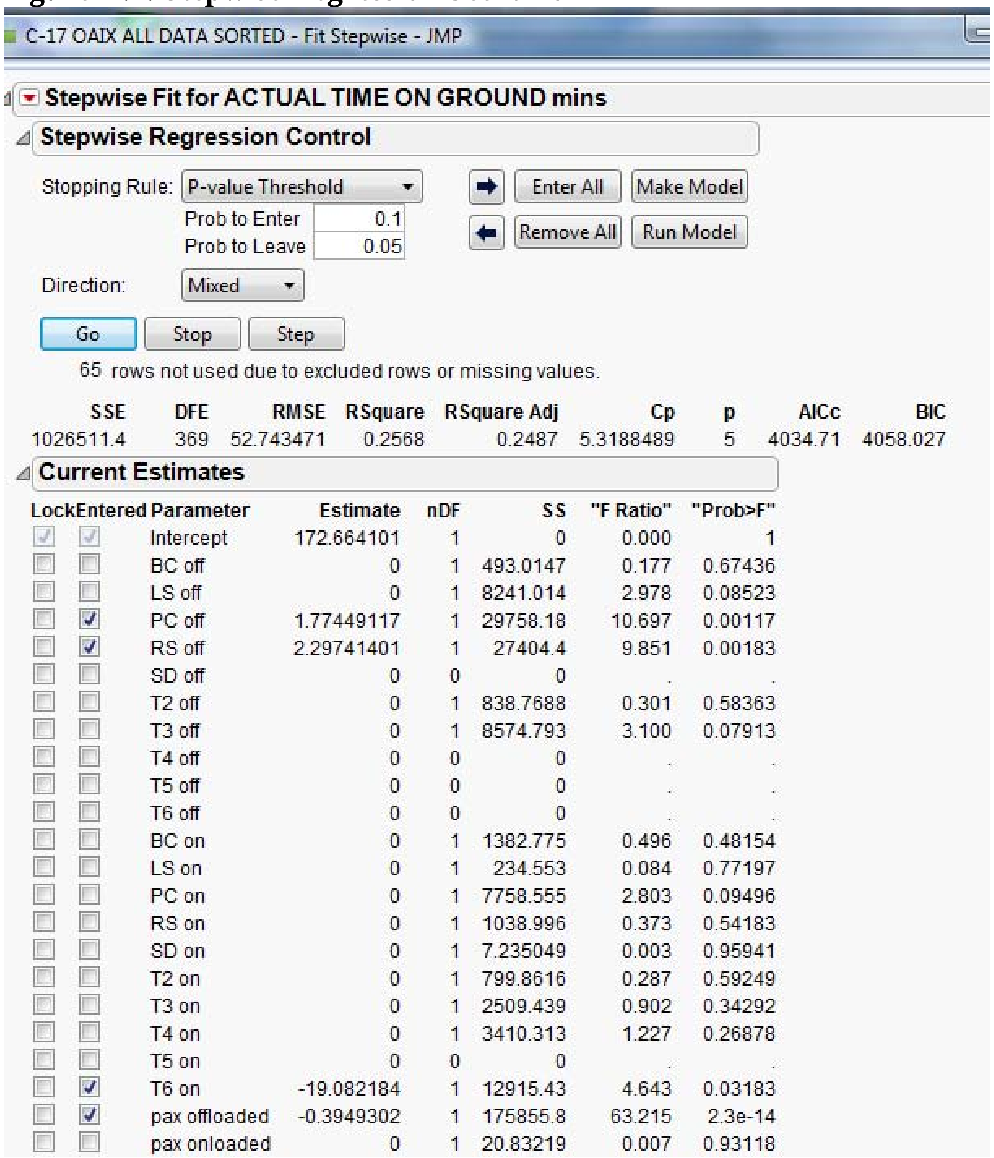
An EXCEL based tool was designed and built for AMC/A9 and TACC planners. This tool is used to predict ground times based on the regression expressions found from the models of three scenarios with significance. Easy to use operations are critical to quickly and effectively planning operations in a wartime environment. The "AMC OEF Ground Time Predictor" has an easy to use interface in the EXCEL program. Any TACC planner can use this tool to predict C-17 ground times at Kandahar AB and Camp Bastion or C-5 ground time at Bagram. The only inputs that are required are the type of aircraft, location, and the equivalent pallet positions for the regressors used in each equation. The remaining regressors are not used and therefore are not included in the tool. This tool is shown in Appendix D.

5.7. Future Research

Proper data collection with a linear regression analysis and models that fits the data more accurately could be re-accomplished for these airfields and aircraft. The research could also be expanded to include all Afghanistan airfields and other airfields in Iraq. This data could also be placed into a much larger model for aircraft throughput. This research could expound on past and current integer programming, simulation, and stochastic techniques. The output from these updated models would yield more accurate airflow through USTRANSCOM’s combat and global environment.

Appendix A: Stepwise Regression Output

Figure A.1. Stepwise Regression Scenario 1



C-17 OAIX ALL DATA SORTED - Fit Stepwise - JMP

Stepwise Fit for ACTUAL TIME ON GROUND mins

Stepwise Regression Control

Stopping Rule: P-value Threshold

Prob to Enter 0.1

Prob to Leave 0.05

Direction: Mixed

Enter All | Make Model | Remove All | Run Model

Go | Stop | Step

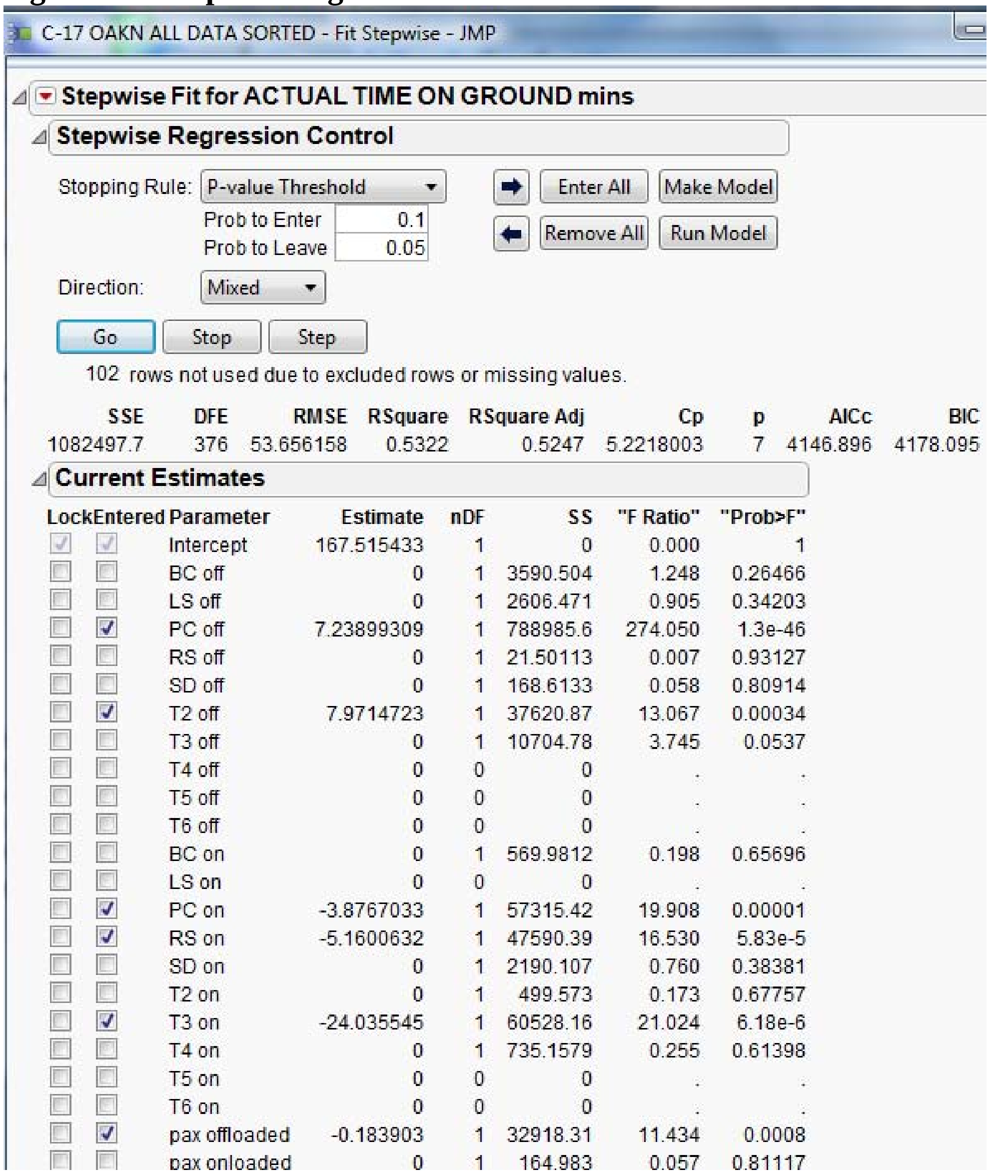
65 rows not used due to excluded rows or missing values.

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
1026511.4	369	52.743471	0.2568	0.2487	5.3188489	5	4034.71	4058.027

Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
✓	✓	Intercept	172.664101	1	0	0.000	1
		BC off	0	1	493.0147	0.177	0.67436
		LS off	0	1	8241.014	2.978	0.08523
	✓	PC off	1.77449117	1	29758.18	10.697	0.00117
	✓	RS off	2.29741401	1	27404.4	9.851	0.00183
		SD off	0	0	0	.	.
		T2 off	0	1	838.7688	0.301	0.58363
		T3 off	0	1	8574.793	3.100	0.07913
		T4 off	0	0	0	.	.
		T5 off	0	0	0	.	.
		T6 off	0	0	0	.	.
		BC on	0	1	1382.775	0.496	0.48154
		LS on	0	1	234.553	0.084	0.77197
		PC on	0	1	7758.555	2.803	0.09496
		RS on	0	1	1038.996	0.373	0.54183
		SD on	0	1	7.235049	0.003	0.95941
		T2 on	0	1	799.8616	0.287	0.59249
		T3 on	0	1	2509.439	0.902	0.34292
		T4 on	0	1	3410.313	1.227	0.26878
		T5 on	0	0	0	.	.
	✓	T6 on	-19.082184	1	12915.43	4.643	0.03183
	✓	pax offloaded	-0.3949302	1	175855.8	63.215	2.3e-14
		pax onloaded	0	1	20.83219	0.007	0.93118

Figure A.2. Stepwise Regression Scenario 2



C-17 OAKN ALL DATA SORTED - Fit Stepwise - JMP

Stepwise Fit for ACTUAL TIME ON GROUND mins

Stepwise Regression Control

Stopping Rule: P-value Threshold

Prob to Enter 0.1

Prob to Leave 0.05

Direction: Mixed

Enter All | Make Model | Remove All | Run Model

Go | Stop | Step

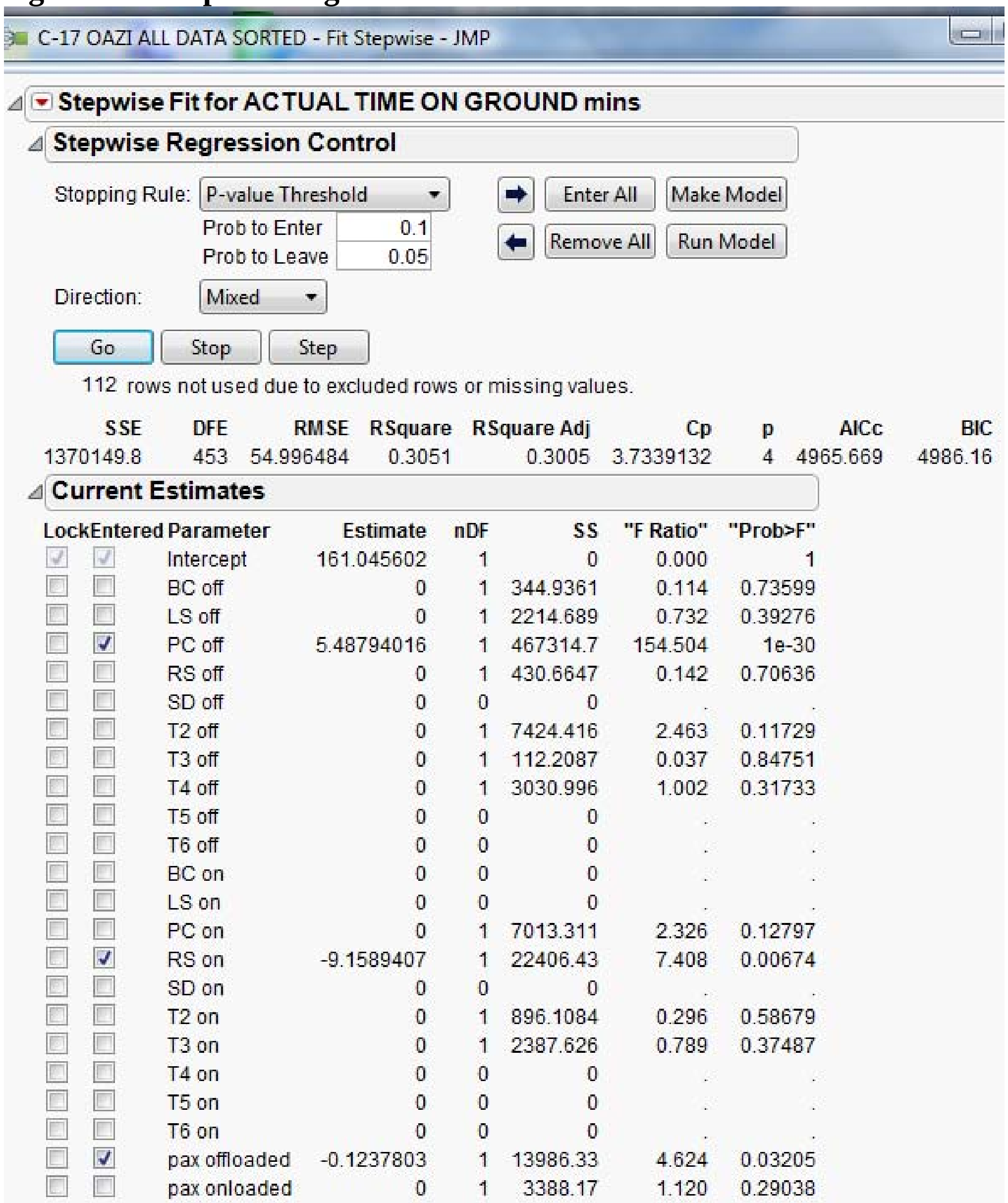
102 rows not used due to excluded rows or missing values.

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
1082497.7	376	53.656158	0.5322	0.5247	5.2218003	7	4146.896	4178.095

Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
✓	✓	Intercept	167.515433	1	0	0.000	1
		BC off	0	1	3590.504	1.248	0.26466
		LS off	0	1	2606.471	0.905	0.34203
	✓	PC off	7.23899309	1	788985.6	274.050	1.3e-46
		RS off	0	1	21.50113	0.007	0.93127
		SD off	0	1	168.6133	0.058	0.80914
	✓	T2 off	7.9714723	1	37620.87	13.067	0.00034
		T3 off	0	1	10704.78	3.745	0.0537
		T4 off	0	0	0	.	.
		T5 off	0	0	0	.	.
		T6 off	0	0	0	.	.
		BC on	0	1	569.9812	0.198	0.65696
		LS on	0	0	0	.	.
	✓	PC on	-3.8767033	1	57315.42	19.908	0.00001
	✓	RS on	-5.1600632	1	47590.39	16.530	5.83e-5
		SD on	0	1	2190.107	0.760	0.38381
		T2 on	0	1	499.573	0.173	0.67757
	✓	T3 on	-24.035545	1	60528.16	21.024	6.18e-6
		T4 on	0	1	735.1579	0.255	0.61398
		T5 on	0	0	0	.	.
		T6 on	0	0	0	.	.
	✓	pax offloaded	-0.183903	1	32918.31	11.434	0.0008
		pax onloaded	0	1	164.983	0.057	0.81117

Figure A.3. Stepwise Regression Scenario 3



C-17 OAZI ALL DATA SORTED - Fit Stepwise - JMP

Stepwise Fit for ACTUAL TIME ON GROUND mins

Stepwise Regression Control

Stopping Rule: P-value Threshold

Prob to Enter 0.1

Prob to Leave 0.05

Enter All | Make Model | Remove All | Run Model

Direction: Mixed

Go | Stop | Step

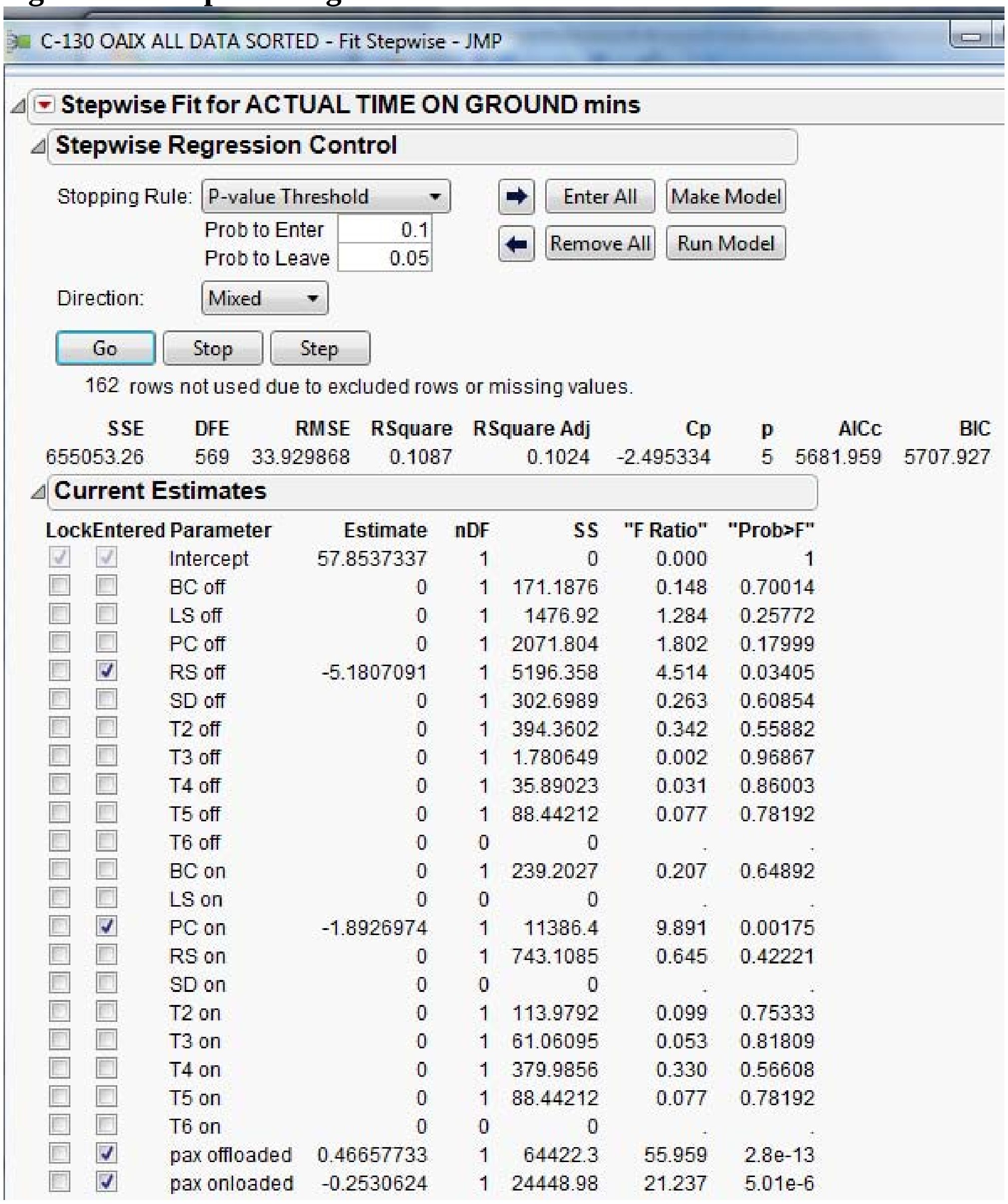
112 rows not used due to excluded rows or missing values.

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
1370149.8	453	54.996484	0.3051	0.3005	3.7339132	4	4965.669	4986.16

Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
☑	☑	Intercept	161.045602	1	0	0.000	1
☐	☐	BC off	0	1	344.9361	0.114	0.73599
☐	☐	LS off	0	1	2214.689	0.732	0.39276
☐	☑	PC off	5.48794016	1	467314.7	154.504	1e-30
☐	☐	RS off	0	1	430.6647	0.142	0.70636
☐	☐	SD off	0	0	0	.	.
☐	☐	T2 off	0	1	7424.416	2.463	0.11729
☐	☐	T3 off	0	1	112.2087	0.037	0.84751
☐	☐	T4 off	0	1	3030.996	1.002	0.31733
☐	☐	T5 off	0	0	0	.	.
☐	☐	T6 off	0	0	0	.	.
☐	☐	BC on	0	0	0	.	.
☐	☐	LS on	0	0	0	.	.
☐	☐	PC on	0	1	7013.311	2.326	0.12797
☐	☑	RS on	-9.1589407	1	22406.43	7.408	0.00674
☐	☐	SD on	0	0	0	.	.
☐	☐	T2 on	0	1	896.1084	0.296	0.58679
☐	☐	T3 on	0	1	2387.626	0.789	0.37487
☐	☐	T4 on	0	0	0	.	.
☐	☐	T5 on	0	0	0	.	.
☐	☐	T6 on	0	0	0	.	.
☐	☑	pax offloaded	-0.1237803	1	13986.33	4.624	0.03205
☐	☐	pax onloaded	0	1	3388.17	1.120	0.29038

Figure A.4. Stepwise Regression Scenario 4



C-130 OAIX ALL DATA SORTED - Fit Stepwise - JMP

Stepwise Fit for ACTUAL TIME ON GROUND mins

Stepwise Regression Control

Stopping Rule: P-value Threshold

Prob to Enter 0.1

Prob to Leave 0.05

Enter All | Make Model | Remove All | Run Model

Direction: Mixed

Go | Stop | Step

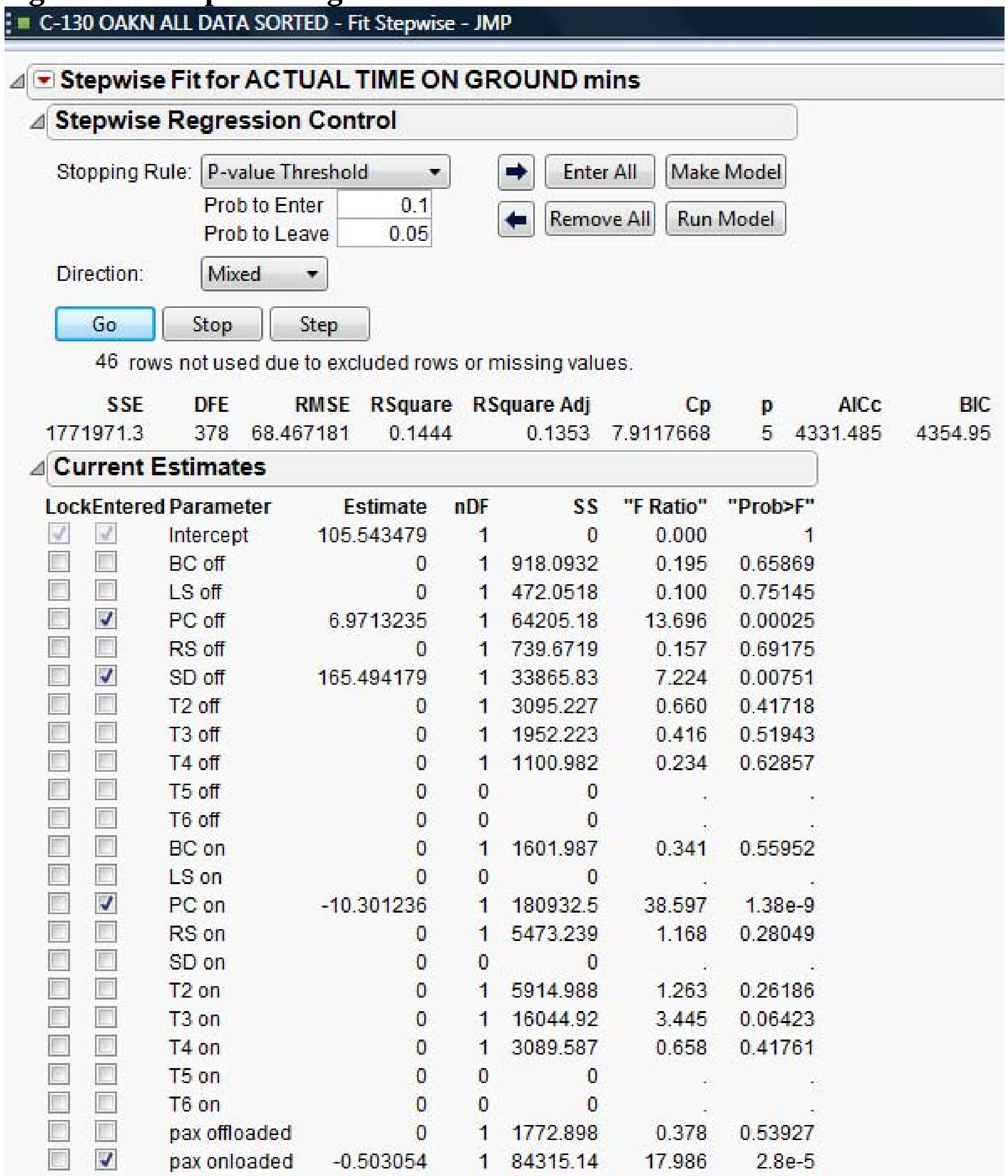
162 rows not used due to excluded rows or missing values.

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
655053.26	569	33.929868	0.1087	0.1024	-2.495334	5	5681.959	5707.927

Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
✓	✓	Intercept	57.8537337	1	0	0.000	1
		BC off	0	1	171.1876	0.148	0.70014
		LS off	0	1	1476.92	1.284	0.25772
		PC off	0	1	2071.804	1.802	0.17999
	✓	RS off	-5.1807091	1	5196.358	4.514	0.03405
		SD off	0	1	302.6989	0.263	0.60854
		T2 off	0	1	394.3602	0.342	0.55882
		T3 off	0	1	1.780649	0.002	0.96867
		T4 off	0	1	35.89023	0.031	0.86003
		T5 off	0	1	88.44212	0.077	0.78192
		T6 off	0	0	0	.	.
		BC on	0	1	239.2027	0.207	0.64892
		LS on	0	0	0	.	.
	✓	PC on	-1.8926974	1	11386.4	9.891	0.00175
		RS on	0	1	743.1085	0.645	0.42221
		SD on	0	0	0	.	.
		T2 on	0	1	113.9792	0.099	0.75333
		T3 on	0	1	61.06095	0.053	0.81809
		T4 on	0	1	379.9856	0.330	0.56608
		T5 on	0	1	88.44212	0.077	0.78192
		T6 on	0	0	0	.	.
	✓	pax offloaded	0.46657733	1	64422.3	55.959	2.8e-13
	✓	pax onloaded	-0.2530624	1	24448.98	21.237	5.01e-6

Figure A.5. Stepwise Regression Scenario 5



C-130 OAKN ALL DATA SORTED - Fit Stepwise - JMP

Stepwise Fit for ACTUAL TIME ON GROUND mins

Stepwise Regression Control

Stopping Rule: P-value Threshold

Prob to Enter 0.1

Prob to Leave 0.05

Enter All | Make Model | Remove All | Run Model

Direction: Mixed

Go | Stop | Step

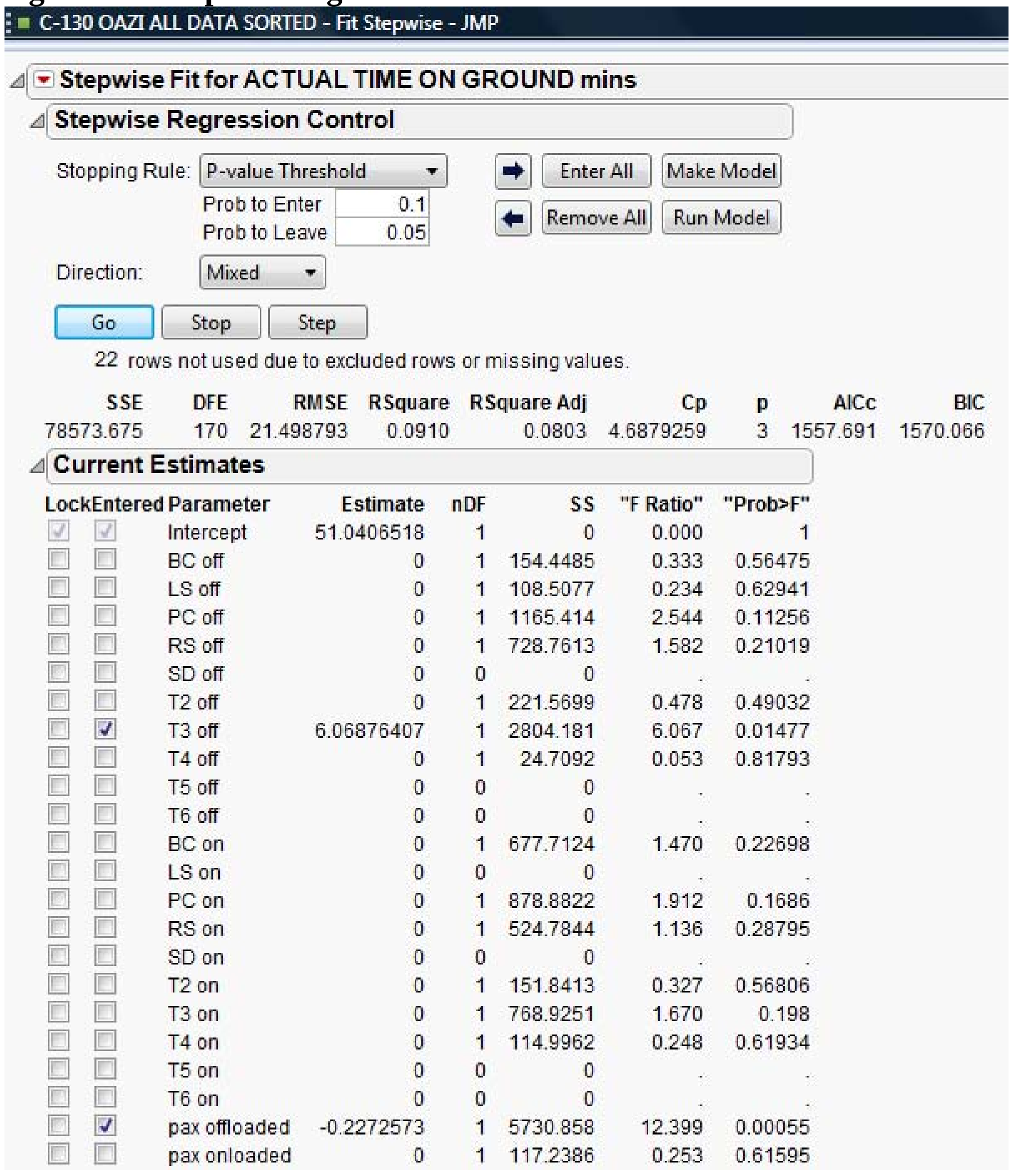
46 rows not used due to excluded rows or missing values.

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
1771971.3	378	68.467181	0.1444	0.1353	7.9117668	5	4331.485	4354.95

Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
☑	☑	Intercept	105.543479	1	0	0.000	1
☐	☐	BC off	0	1	918.0932	0.195	0.65869
☐	☐	LS off	0	1	472.0518	0.100	0.75145
☐	☑	PC off	6.9713235	1	64205.18	13.696	0.00025
☐	☐	RS off	0	1	739.6719	0.157	0.69175
☐	☑	SD off	165.494179	1	33865.83	7.224	0.00751
☐	☐	T2 off	0	1	3095.227	0.660	0.41718
☐	☐	T3 off	0	1	1952.223	0.416	0.51943
☐	☐	T4 off	0	1	1100.982	0.234	0.62857
☐	☐	T5 off	0	0	0	.	.
☐	☐	T6 off	0	0	0	.	.
☐	☐	BC on	0	1	1601.987	0.341	0.55952
☐	☐	LS on	0	0	0	.	.
☐	☑	PC on	-10.301236	1	180932.5	38.597	1.38e-9
☐	☐	RS on	0	1	5473.239	1.168	0.28049
☐	☐	SD on	0	0	0	.	.
☐	☐	T2 on	0	1	5914.988	1.263	0.26186
☐	☐	T3 on	0	1	16044.92	3.445	0.06423
☐	☐	T4 on	0	1	3089.587	0.658	0.41761
☐	☐	T5 on	0	0	0	.	.
☐	☐	T6 on	0	0	0	.	.
☐	☐	pax offloaded	0	1	1772.898	0.378	0.53927
☐	☑	pax onloaded	-0.503054	1	84315.14	17.986	2.8e-5

Figure A.6. Stepwise Regression Scenario 6



C-130 OAZI ALL DATA SORTED - Fit Stepwise - JMP

Stepwise Fit for ACTUAL TIME ON GROUND mins

Stepwise Regression Control

Stopping Rule: P-value Threshold

Prob to Enter 0.1

Prob to Leave 0.05

Direction: Mixed

Enter All | Make Model | Remove All | Run Model

Go | Stop | Step

22 rows not used due to excluded rows or missing values.

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
78573.675	170	21.498793	0.0910	0.0803	4.6879259	3	1557.691	1570.066

Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
✓	✓	Intercept	51.0406518	1	0	0.000	1
		BC off	0	1	154.4485	0.333	0.56475
		LS off	0	1	108.5077	0.234	0.62941
		PC off	0	1	1165.414	2.544	0.11256
		RS off	0	1	728.7613	1.582	0.21019
		SD off	0	0	0	.	.
		T2 off	0	1	221.5699	0.478	0.49032
	✓	T3 off	6.06876407	1	2804.181	6.067	0.01477
		T4 off	0	1	24.7092	0.053	0.81793
		T5 off	0	0	0	.	.
		T6 off	0	0	0	.	.
		BC on	0	1	677.7124	1.470	0.22698
		LS on	0	0	0	.	.
		PC on	0	1	878.8822	1.912	0.1686
		RS on	0	1	524.7844	1.136	0.28795
		SD on	0	0	0	.	.
		T2 on	0	1	151.8413	0.327	0.56806
		T3 on	0	1	768.9251	1.670	0.198
		T4 on	0	1	114.9962	0.248	0.61934
		T5 on	0	0	0	.	.
		T6 on	0	0	0	.	.
	✓	pax offloaded	-0.2272573	1	5730.858	12.399	0.00055
		pax onloaded	0	1	117.2386	0.253	0.61595

Figure A.7. Stepwise Regression Scenario 7

C-5 OAIX ALL DATA SORTED - Fit Stepwise - JMP

Stepwise Fit for ACTUAL TIME ON GROUND mins

Stepwise Regression Control

Stopping Rule: P-value Threshold

Prob to Enter 0.1

Prob to Leave 0.05

Enter All | Make Model | Remove All | Run Model

Direction: Mixed

Go | Stop | Step

3 rows not used due to excluded rows or missing values.

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
77269.109	21	60.658729	0.4865	0.4376	1.7517174	3	272.0622	274.6692

Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
☑	☑	Intercept	364.387482	1	0	0.000	1
☐	☑	BC off	-15.808685	1	60059.4	16.323	0.00059
☐	☐	LS off	0	0	0	.	.
☐	☑	PC off	-3.5684651	1	21704.38	5.899	0.02422
☐	☐	RS off	0	1	1460.429	0.385	0.54179
☐	☐	SD off	0	0	0	.	.
☐	☐	T2 off	0	1	662.9796	0.173	0.68181
☐	☐	T3 off	0	1	3487.181	0.945	0.34254
☐	☐	T4 off	0	1	2.967447	0.001	0.97816
☐	☐	T5 off	0	1	854.2207	0.224	0.64145
☐	☐	T6 off	0	0	0	.	.
☐	☐	BC on	0	0	0	.	.
☐	☐	LS on	0	1	3674.59	0.999	0.32959
☐	☐	PC on	0	1	1158.55	0.304	0.58723
☐	☐	RS on	0	1	4899.201	1.354	0.25829
☐	☐	SD on	0	0	0	.	.
☐	☐	T2 on	0	0	0	.	.
☐	☐	T3 on	0	0	0	.	.
☐	☐	T4 on	0	0	0	.	.
☐	☐	T5 on	0	0	0	.	.
☐	☐	T6 on	0	0	0	.	.
☐	☐	pax offloaded	0	0	0	.	.
☐	☐	pax onloaded	0	1	1798.602	0.477	0.49788

Figure A.8. Stepwise Regression Scenario 8

C-5 OAKN ALL DATA SORTED - Fit Stepwise - JMP

Stepwise Fit for ACTUAL TIME ON GROUND mins

Stepwise Regression Control

Stopping Rule: P-value Threshold

Prob to Enter 0.1

Prob to Leave 0.05

Direction: Mixed

Enter All | Make Model | Remove All | Run Model

Go | Stop | Step

5 rows not used due to excluded rows or missing values.

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
141236.42	42	57.989412	-0.000	-0.0000	-4.676248	1	474.4993	477.7217

Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
✓	✓	Intercept	266.116279	1	0	0.000	1
		BC off	0	0	0	.	.
		LS off	0	0	0	.	.
		PC off	0	1	0.085533	0.000	0.99605
		RS off	0	1	955.3787	0.279	0.60006
		SD off	0	0	0	.	.
		T2 off	0	1	455.6042	0.133	0.71753
		T3 off	0	1	40.79238	0.012	0.91386
		T4 off	0	1	154.2657	0.045	0.83336
		T5 off	0	0	0	.	.
		T6 off	0	1	15.44241	0.004	0.94694
		BC on	0	0	0	.	.
		LS on	0	0	0	.	.
		PC on	0	1	854.1329	0.249	0.62013
		RS on	0	0	0	.	.
		SD on	0	0	0	.	.
		T2 on	0	0	0	.	.
		T3 on	0	0	0	.	.
		T4 on	0	1	854.1329	0.249	0.62013
		T5 on	0	0	0	.	.
		T6 on	0	0	0	.	.
		pax offloaded	0	1	796.0138	0.232	0.63232
		pax onloaded	0	1	8123.281	2.502	0.12138

Appendix B: Standard Least Squares Output

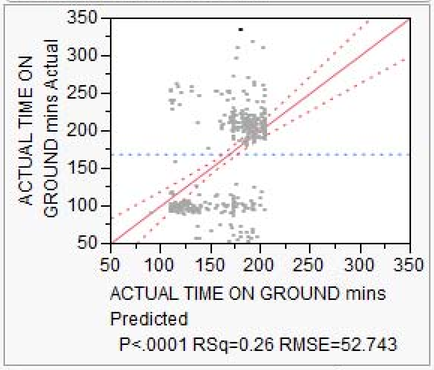
Figure B.1. Scenario 1

C-17 OAIX ALL DATA SORTED - Fit Least Squares - JMP

Response ACTUAL TIME ON GROUND mins

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.256776
RSquare Adj	0.24872
Root Mean Square Error	52.74347
Mean of Response	168.8289
Observations (or Sum Wgts)	374

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	354649.6	88662.4	31.8715
Error	369	1026511.4	2781.9	Prob > F
C. Total	373	1381161.0		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	207	637380.8	3079.13	1.2819
Pure Error	162	389130.6	2402.04	Prob > F
				0.0489*
Total Error	369	1026511.4		Max RSq
				0.7183

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	172.6641	5.307362	32.53	<.0001*
PC off	1.7744912	0.54255	3.27	0.0012*
RS off	2.297414	0.731978	3.14	0.0018*
T6 on	-19.08218	8.856097	-2.15	0.0318*
pax offloaded	-0.39493	0.049672	-7.95	<.0001*

Effect Tests

Residual by Predicted Plot

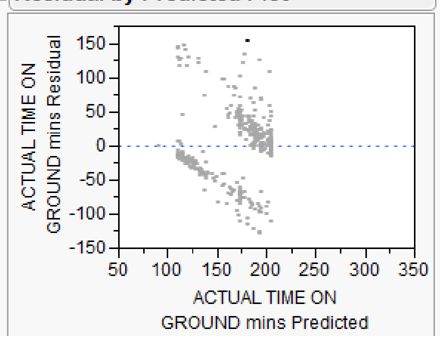


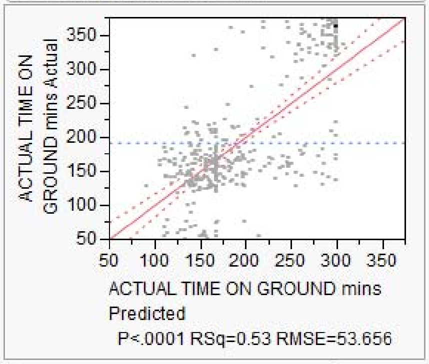
Figure B.2. Scenario 2

C-17 OAKN ALL DATA SORTED - Fit Least Squares - JMP

Response ACTUAL TIME ON GROUND mins

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.532187
RSquare Adj	0.524721
Root Mean Square Error	53.65616
Mean of Response	191.624
Observations (or Sum Wgts)	383

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	1231454.1	205242	71.2899
Error	376	1082497.7	2879	Prob > F
C. Total	382	2313951.9		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
				0.8363
Lack Of Fit	226	603514.2	2670.42	Prob > F
Pure Error	150	478983.6	3193.22	0.8879
Total Error	376	1082497.7		Max RSq
				0.7930

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	167.51543	4.775189	35.08	<.0001*
PC off	7.2389931	0.437284	16.55	<.0001*
T2 off	7.9714723	2.205178	3.61	0.0003*
PC on	-3.876703	0.868853	-4.46	<.0001*
RS on	-5.160063	1.269156	-4.07	<.0001*
T3 on	-24.03554	5.241973	-4.59	<.0001*
pax offloaded	-0.183903	0.054386	-3.38	0.0008*

Effect Tests

Residual by Predicted Plot

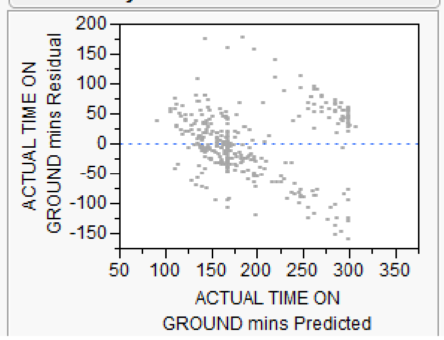


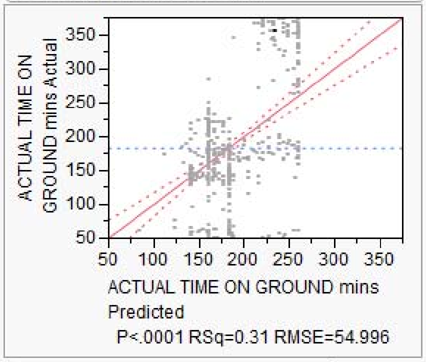
Figure B.3. Scenario 3

C-17 OAZI ALL DATA SORTED - Fit Least Squares - JMP

Response ACTUAL TIME ON GROUND mins

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.305066
RSquare Adj	0.300464
Root Mean Square Error	54.99648
Mean of Response	183.1422
Observations (or Sum Wgts)	457

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	601475.9	200492	66.2868
Error	453	1370149.8	3025	Prob > F
C. Total	456	1971625.8		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	104	649438.2	6244.60	3.0239
Pure Error	349	720711.7	2065.08	Prob > F
Total Error	453	1370149.8		<.0001*
				Max RSq
				0.6345

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	161.0456	3.641807	44.22	<.0001*
PC off	5.4879402	0.441509	12.43	<.0001*
RS on	-9.158941	3.365068	-2.72	0.0067*
pax offloaded	-0.12378	0.057562	-2.15	0.0321*

Effect Tests

Residual by Predicted Plot

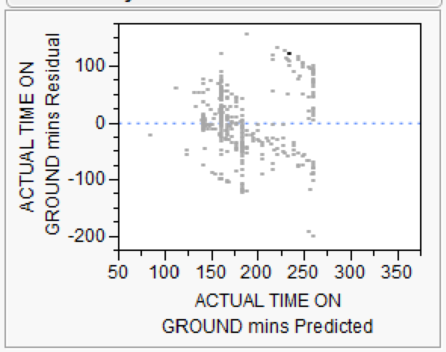


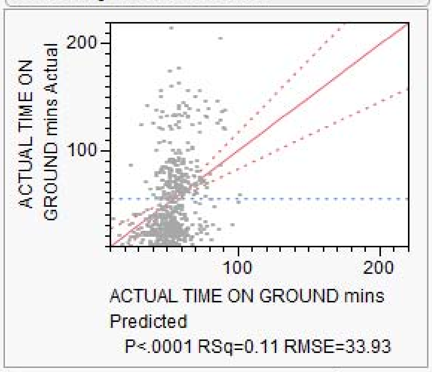
Figure B.4. Scenario 4

C-130 OAIX ALL DATA SORTED - Fit Least Squares - JMP

Response ACTUAL TIME ON GROUND mins

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.108679
RSquare Adj	0.102413
Root Mean Square Error	33.92987
Mean of Response	54.74042
Observations (or Sum Wgts)	574

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	79871.06	19967.8	17.3446
Error	569	655053.26	1151.2	**Prob > F**
C. Total	573	734924.32		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
				0.8419
Lack Of Fit	445	492159.31	1105.98	**Prob > F**
Pure Error	124	162893.96	1313.66	0.8931
Total Error	569	655053.26		**Max RSq**
				0.7784

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	57.853734	2.371516	24.40	<.0001*
RS off	-5.180709	2.438495	-2.12	0.0341*
PC on	-1.892697	0.601825	-3.14	0.0017*
pax offloaded	0.4665773	0.062372	7.48	<.0001*
pax onloaded	-0.253062	0.054914	-4.61	<.0001*

Effect Tests

Residual by Predicted Plot

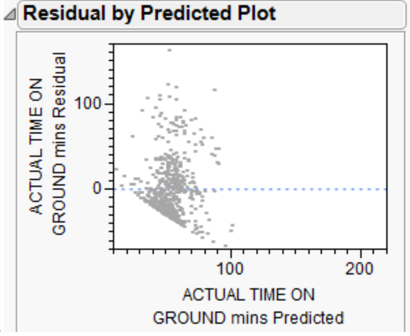


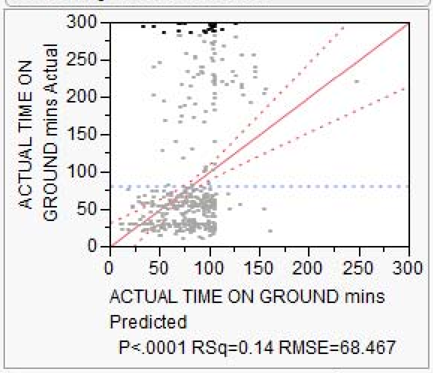
Figure B.5. Scenario 5

C-130 OAKN ALL DATA SORTED - Fit Least Squares - JMP

Response ACTUAL TIME ON GROUND mins

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.144396
RSquare Adj	0.135342
Root Mean Square Error	68.46718
Mean of Response	81.14883
Observations (or Sum Wgts)	383

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	299047.2	74761.8	15.9483
Error	378	1771971.3	4687.8	Prob > F
C. Total	382	2071018.5		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
				0.7344
Lack Of Fit	273	1162912.4	4259.75	Prob > F
Pure Error	105	609058.9	5800.56	0.9752
Total Error	378	1771971.3		Max RSq
				0.7059

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	105.54348	5.639337	18.72	<.0001*
PC off	6.9713235	1.883704	3.70	0.0002*
SD off	165.49418	61.57215	2.69	0.0075*
PC on	-10.30124	1.658111	-6.21	<.0001*
pax onloaded	-0.503054	0.118616	-4.24	<.0001*

Effect Tests

Residual by Predicted Plot

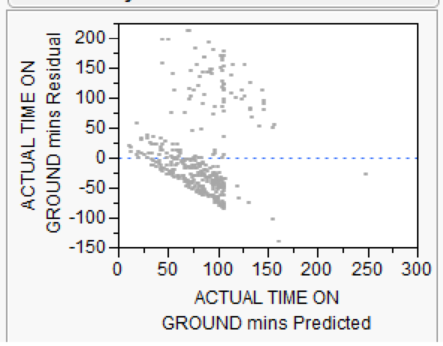


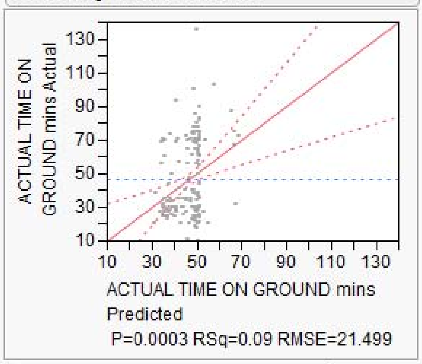
Figure B.6. Scenario 6

C-130 OAZI ALL DATA SORTED - Fit Least Squares - JMP

Response ACTUAL TIME ON GROUND mins

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.090991
RSquare Adj	0.080297
Root Mean Square Error	21.49879
Mean of Response	46.45087
Observations (or Sum Wgts)	173

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	7865.157	3932.58	8.5084
Error	170	78573.675	462.20	Prob > F
C. Total	172	86438.832		0.0003*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
				0.8675
Lack Of Fit	65	27453.105	422.355	Prob > F
Pure Error	105	51120.570	486.863	0.7303
Total Error	170	78573.675		Max RSq
				0.4086

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	51.040652	2.276191	22.42	<.0001*
T3 off	6.0687641	2.463833	2.46	0.0148*
pax offloaded	-0.227257	0.064539	-3.52	0.0006*

Effect Tests

Residual by Predicted Plot

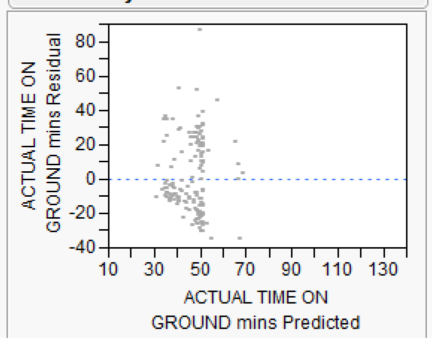


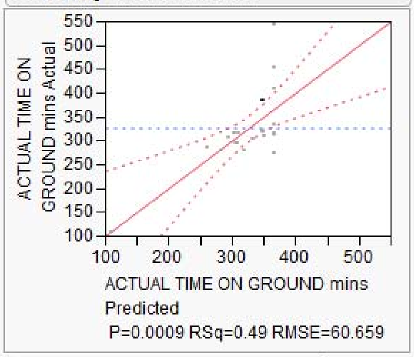
Figure B.7. Scenario 7

C-5 OAIX ALL DATA SORTED - Fit Least Squares - JMP

Response ACTUAL TIME ON GROUND mins

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.486525
RSquare Adj	0.437622
Root Mean Square Error	60.65873
Mean of Response	327.125
Observations (or Sum Wgts)	24

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	73213.52	36606.8	9.9489
Error	21	77269.11	3679.5	Prob > F
C. Total	23	150482.63		0.0009*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
				0.0936
Lack Of Fit	10	6060.209	606.02	Prob > F
Pure Error	11	71208.900	6473.54	0.9996
Total Error	21	77269.109		Max RSq
				0.5268

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	364.38748	16.86271	21.61	<.0001*
BC off	-15.80868	3.912898	-4.04	0.0006*
PC off	-3.568465	1.469268	-2.43	0.0242*

Effect Tests

Residual by Predicted Plot

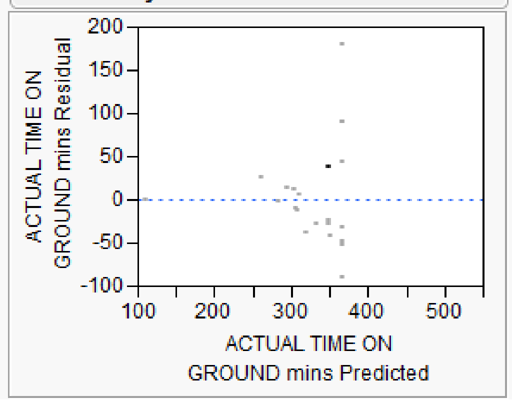


Figure B.8. Scenario 8

No regressors included in stepwise regression.

APPENDIX C: Square Root Transformation on Y variable

Standard Least Squares Output applied with the square root transformation on Y variable

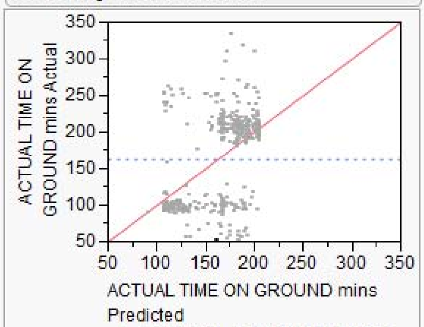
Figure C.1. Scenario 1

C-17 OAIX ALL DATA SORTED - Fit Least Squares 2 - JMP

Response Sqrt(ACTUAL TIME ON GROUND mins)

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.270623
RSquare Adj	0.262717
Root Mean Square Error	2.099443
Mean of Response	12.76192
Observations (or Sum Wgts)	374

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	603.4585	150.865	34.2278
Error	369	1626.4273	4.408	Prob > F
C. Total	373	2229.8858		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
				1.3182
Lack Of Fit	207	1020.5353	4.93012	Prob > F
Pure Error	162	605.8920	3.74007	0.0329*
Total Error	369	1626.4273		Max RSq
				0.7283

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	12.894344	0.211258	61.04	<.0001*
PC off	0.0738719	0.021596	3.42	0.0007*
RS off	0.1002212	0.029136	3.44	0.0006*
T6 on	-0.795486	0.352515	-2.26	0.0246*
pax offloaded	-0.016061	0.001977	-8.12	<.0001*

Effect Tests

Residual by Predicted Plot

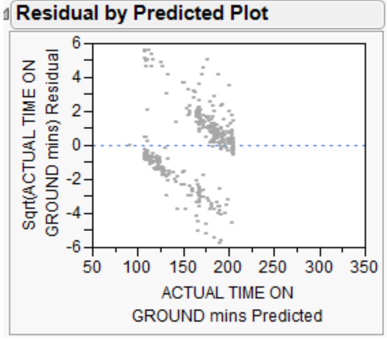


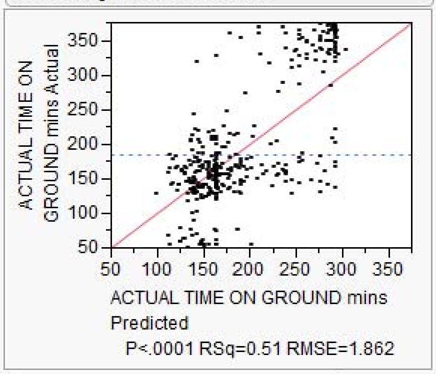
Figure C.2. Scenario 2

C-17 OAKN ALL DATA SORTED - Fit Least Squares 2 - JMP

Response Sqrt(ACTUAL TIME ON GROUND mins)

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.512264
RSquare Adj	0.504481
Root Mean Square Error	1.862015
Mean of Response	13.58843
Observations (or Sum Wgts)	383

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	1369.1898	228.198	65.8182
Error	376	1303.6291	3.467	Prob > F
C. Total	382	2672.8189		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
				0.9817
Lack Of Fit	226	777.7709	3.44146	Prob > F
Pure Error	150	525.8582	3.50572	0.5534
Total Error	376	1303.6291		Max RSq
				0.8033

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	12.82002	0.165712	77.36	<.0001*
PC off	0.238186	0.015175	15.70	<.0001*
T2 off	0.2657309	0.076526	3.47	0.0006*
PC on	-0.119009	0.030152	-3.95	<.0001*
RS on	-0.196195	0.044043	-4.45	<.0001*
T3 on	-0.84792	0.181911	-4.66	<.0001*
pax offloaded	-0.00664	0.001887	-3.52	0.0005*

Effect Tests

Residual by Predicted Plot

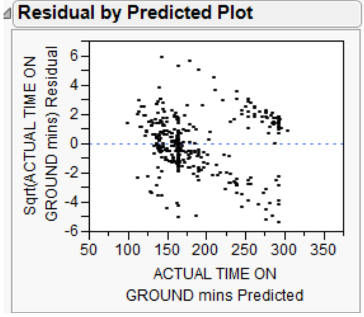


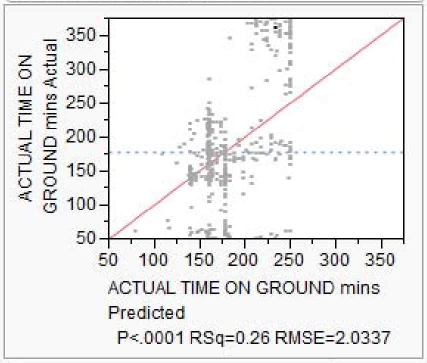
Figure C.3. Scenario 3

C-17 OAZI ALL DATA SORTED - Fit Least Squares 2 - JMP

Response Sqrt(ACTUAL TIME ON GROUND mins)

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.263313
RSquare Adj	0.258435
Root Mean Square Error	2.033715
Mean of Response	13.3258
Observations (or Sum Wgts)	457

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	669.6815	223.227	53.9718
Error	453	1873.6071	4.136	Prob > F
C. Total	456	2543.2886		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
				3.0961
Lack Of Fit	104	899.0958	8.64515	Prob > F
Pure Error	349	974.5112	2.79230	<.0001*
Total Error	453	1873.6071		Max RSq
				0.6168

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	12.648464	0.13467	93.92	<.0001*
PC off	0.1762295	0.016327	10.79	<.0001*
RS on	-0.407742	0.124437	-3.28	0.0011*
pax offloaded	-0.005161	0.002129	-2.42	0.0157*

Effect Tests

Residual by Predicted Plot

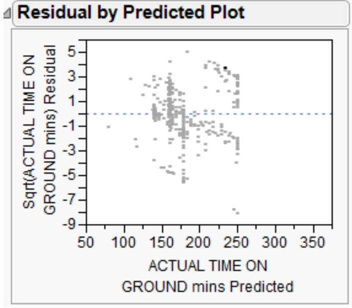


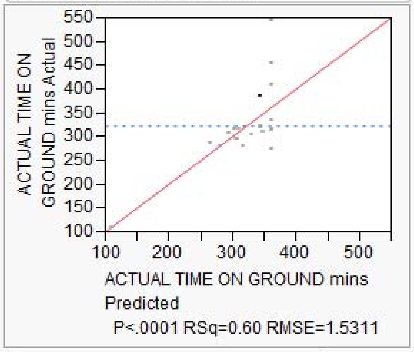
Figure C.4. Scenario 7

C-5 OAIX ALL DATA SORTED - Fit Least Squares 2 - JMP

Response Sqrt(ACTUAL TIME ON GROUND mins)

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.604635
RSquare Adj	0.566981
Root Mean Square Error	1.531069
Mean of Response	17.9426
Observations (or Sum Wgts)	24

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	75.28421	37.6421	16.0577
Error	21	49.22764	2.3442	Prob > F
C. Total	23	124.51185		<.0001*

Lack Of Fit

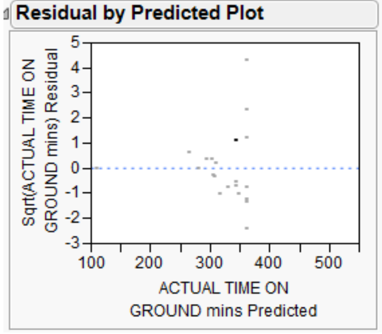
Source	DF	Sum of Squares	Mean Square	F Ratio
				0.0991
Lack Of Fit	10	4.068852	0.40689	Prob > F
Pure Error	11	45.158787	4.10534	0.9995
Total Error	21	49.227639		Max RSq
				0.6373

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	18.9939	0.425627	44.63	<.0001*
BC off	-0.531826	0.098764	-5.38	<.0001*
PC off	-0.092356	0.037085	-2.49	0.0212*

Effect Tests

Residual by Predicted Plot



APPENDIX D: EXCEL BASED TACC TOOL

Ground time predictor

1) select aircraft and airfield from drop down box
2) input equivalent pallet positions and number of passengers (only needed types for prediction are included)
3) ground time appears in minutes and hours

Selection	BC off	PC off	RS off	T2 off	PC on	RS on	T3 on	T6 on	Pax off
C-17 OAZI	0	9	0	0	2	9	0	0	40

Ground Time	107.30	minutes
	1.79	hours

Definitions
BC off = Belly cargo offloaded
PC off = Palletized cargo offloaded
RS off = Rolling stock cargo offloaded
T2 off = Pallet Train of 2 offloaded; 1 T2 = 1 for model
PC on = Palletized cargo onloaded
RS on = Rolling Stock cargo onloaded
T3 on = Pallet Train of 3 onloaded; 1 T3 = 1 for model
T6 on = Pallet Train of 6 onloaded; 1 T6 = 1 for model
Pax off = # of total passengers offloaded

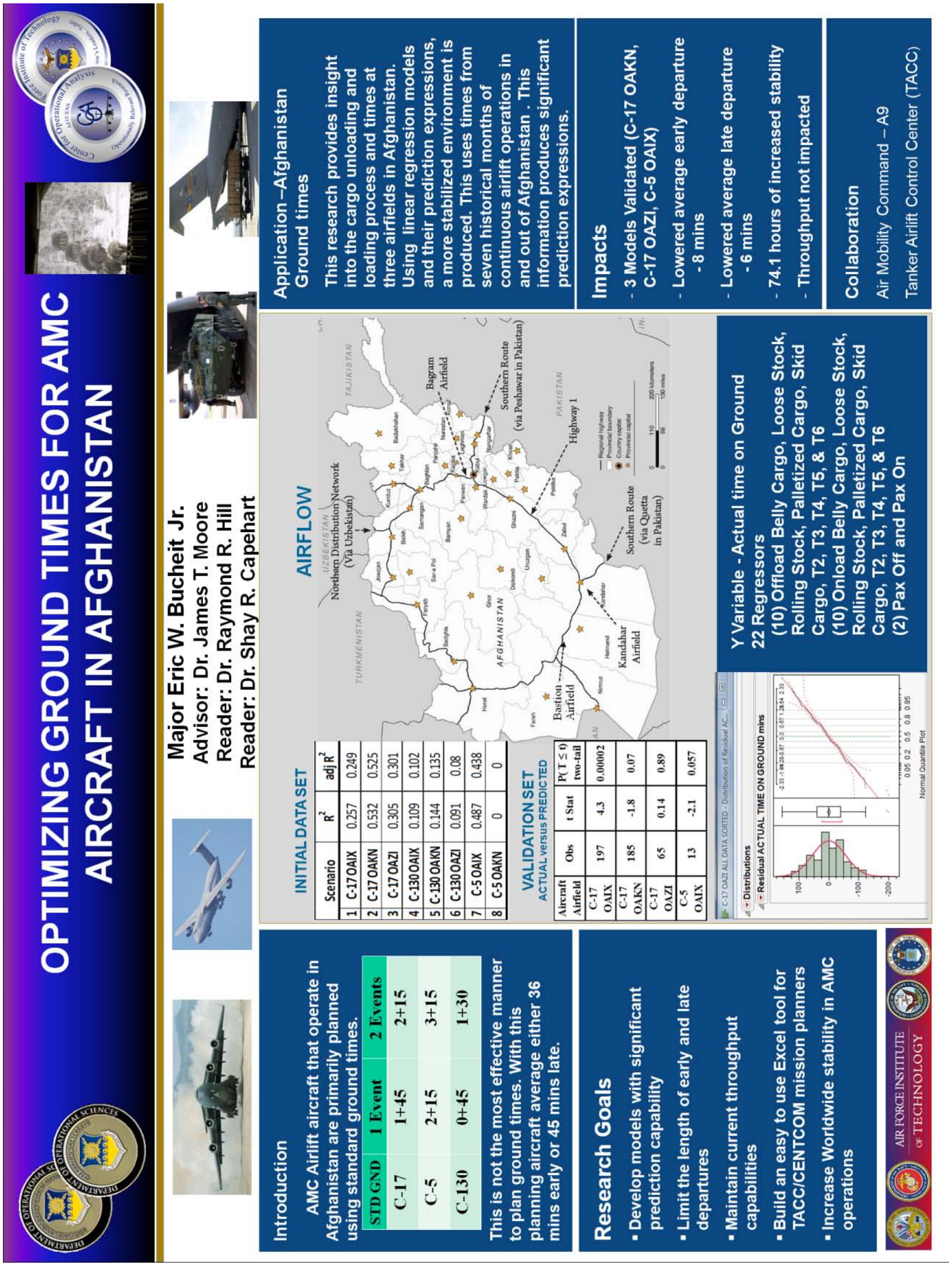
APPENDIX E: Blue Dart

OPTIMIZING GROUND TIMES FOR AMC AIRCRAFT IN AFGHANISTAN

Air Mobility Command's (AMC) airlift assets that transit airfields in Afghanistan are given only a small variety of ground times in order to accomplish their mission. These ground times are based on overarching categories of missions that aircraft execute, such as cargo upload, cargo download, passenger upload, passenger download, or a combination of these. The current mission planning system uses these overarching categories to plan ground times and does not account for the exact amount of cargo or passengers. This leads to longer or shorter ground times than planned. In order to increase stability at these fields and better account for the number of sorties that can be planned into Afghanistan, a method to calculate optimal or near optimal ground times is needed.

This research creates a linear regression model that accounts for the size of cargo upload, cargo download, passenger upload, and passenger download known by the mission planner. This model can be used by the mission planners at AMC's Tanker Airlift Control Center (TACC) to increase the efficiency at which they plan sorties. Eight scenarios are analyzed to account for C-17, C-130 and C-5 missions to Bagram AB, Kandahar AB and Camp Bastion airfields in Afghanistan. Three of the scenario models are found to be significant and are validated with split data from a separate months worth of data. The use of the three significant models will increase stability in AMC planning and efficiency. This occurs by reducing early and late times by an average of seven minutes per mission. This increases stability planning by 74.1 hours per month. In turn, our overall wartime effectiveness will be enhanced.

APPENDIX F: Summary Chart



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Vita

Major Eric W. Bucheit Jr. graduated from McDowell High School in Erie, Pa in 1995. He entered undergraduate studies at the United States Air Force Academy in Colorado Springs, Colorado where he graduated with a Bachelor of Science degree in Mechanical Engineering in June 1999 and received his commission as an Air Force officer. He then entered Joint Specialized Undergraduate Pilot Training at Laughlin Air Force Base in Del Rio, Texas where he met his future wife, graduated in February 2001and earned his assignment to Charleston Air Force Base, Charleston, South Carolina to pilot the C-17. Major Bucheit married Heidi during his tenure at Charleston AFB. After flying C-17 missions into Afghanistan in support of Operation Enduring Freedom, and continually trying to earn an assignment with his wife, who was a KC-135 pilot at McConnell AFB, KS. They both chose to become initial cadre for the RQ-4A Global Hawk to collocated at Beale AFB, CA. Major Bucheit commanded the Global Hawk in support of Operation Iraqi Freedom and Operation Enduring Freedom. He and his wife then chose to fly the C-17 out of Charleston Air Force Base, Charleston, South Carolina. In August 2009, he entered the Graduate School of Engineering and Management, Air Force Institute of Technology. Upon graduation, he will be assigned to the HQ USAF/A5.

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14. ABSTRACT This research provides insight into the cargo unloading and loading process and times at three airfields in Afghanistan. Using a linear regression model and its prediction capability, a more stabilized environment is produced. This uses the times from seven historical months of continuous operations in Afghanistan and uses this information for the prediction expressions. Using this model, no throughput is lowered and early and late times are lowered by an average of seven minutes per mission. Over the course of a month, this increases planning stability by 74.1 hours. This not only impacts the planning at the downrange location, but also impacts worldwide operations and cargo movement.

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